RESPONDENT RECRUITMENT TO CONSECUTIVE TRAVEL SURVEYS: EXPLORING SAMPLE REPRESENTATIVENESS AND TRAVEL BEHAVIOR MODEL QUALITY USING SAMPLE SELECTION MODELS

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RESPONDENT RECRUITMENT TO CONSECUTIVE TRAVEL SURVEYS: EXPLORING SAMPLE REPRESENTATIVENESS AND TRAVEL BEHAVIOR MODEL QUALITY USING SAMPLE SELECTION MODELS

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LIST OF SYMBOLS AND ABBREVIATIONS

GDOT survey	Georgia Department of Transportation Emerging Technologies Survey
NHTS	National Household Travel Survey
PSS	Probit with sample selection
SS	Sample selection
VMD	Vehicle-miles driven

SUMMARY

Declining survey response rates have increased the costs of travel survey recruitment. Recruiting respondents based on their expressed willingness to participate in future surveys, obtained from a preceding survey, is a potential solution but may exacerbate sample biases. In this thesis, we analyze self-selection biases of survey respondents recruited from the 2017 U.S. National Household Travel Survey (NHTS), who had agreed to be contacted again for follow-up surveys. We apply a probit with sample selection (PSS) model to analyze respondents' willingness to participate in a follow-up survey and their actual response behavior once contacted. Results verify the existence of self-selection biases, which are related to survey burden, sociodemographic characteristics, travel behavior, and item non-response to sensitive variables. The PSS model is then validated using a hold-out sample and applied to the NHTS samples from various geographic regions to predict follow-up survey participation. Effect size indicators suggest that resulting samples may be most biased along age and education dimensions. We further summarized six model performance measures based on the PSS model structure. Lastly, we analyze the consequence of self-selection biases by assessing their influence on travel behavior models developed on the sample recruited through the proposed method. We recommend applying the sample selection model to correct for such biases when the data are available. Otherwise, sample weights should be applied when the unweighted sample would produce inconsistent coefficient estimates. However, if the Hausman test supports the consistency of the estimated parameters, unweighted regression models should be preferred to avoid inefficient estimates.

Overall, this study provides insight into the self-selection biases associated with respondents recruited from preceding travel surveys. The PSS model results can help researchers better understand and address such biases, while the nuanced application of various model measures lays a foundation for appropriate comparison across sample selection models. This is the first study, to our knowledge, that uses the PSS model to analyze sample biases residing in consecutive survey recruitment.

CHAPTER 1. INTRODUCTION

High-quality survey data provide the foundation for research and policymaking across many fields. While novel data sources are actively being examined for use in transport applications, both currently and for the foreseeable future traditional travel surveys will continue to play an irreplaceable role in providing critical data for use in travel demand modeling, regional planning, and policymaking. However, survey response rates are in continuous and significant decline, thus requiring increased efforts toward respondent recruitment. Further necessitating these increased efforts is the fact that low response rates and their accompanying nonresponse biases can threaten the validity of survey data, and thus contingent research findings (National Research Council, 2013).

Survey teams have employed a range of efforts aimed at increasing response rates and improving survey data quality. One of the most common tools is the use of passive datasets such as GPS records (Bohte and Maat, 2009), targeted marketing data (Shaw et al., 2019)), novel survey formats (e.g., interactive surveys; Collins et al., 2012), and targeted sampling frames (e.g., online panels; Circella et al., 2016), to name a few. Among these efforts, another approach, which is the focus of this thesis, is to *recruit survey respondents who had expressed willingness to be contacted again in a previous survey*; this approach has been shown to produce a significantly higher response rate and lower cost per valid response relative to random sampling (Amarov and Rendtel, 2013; Kim et al., 2019; Circella et al., 2020).

This recruitment method is similar to the approach used in panel studies in that both recruit respondents from preceding surveys. The differences, however, reside in the survey purpose, contents, or outcome. Specifically, panel surveys focus on repeated observations on a set of variables for the same sample unit over time (Lavrakas, 2008), which allows the tracking of specific variables or study interests. Moreover, since panel surveys recruit the same respondents periodically, it also introduces attrition biases. In contrast, recruiting respondents from a previous survey is not a periodical behavior. The use of this recruitment method: (1) increases the survey response rates obtained on follow-up surveys; (2) reduces the financial burden for local transportation agencies and researchers; and (3) facilitates the *expansion* of the variable set of the preceding survey and enables data fusion across datasets (Shaw et al., 2020).

However, in the transportation domain, this recruitment method has not been widely adopted nor carefully examined. A major potential drawback of recruiting respondents based on their willingness expressed in a preceding survey is the non-representativeness that may be inherent in that sample (Couper et al., 2007). Accordingly, the present thesis is interested in the following questions: (1) Who is more likely to respond to a follow-up survey? (2) How does recruiting respondents based on their willingness expressed in a preceding travel survey bias the follow-up survey sample? (3) What survey sample could we expect if we recruited respondents from the 2017 NHTS respondents in different geographic regions in the U.S.? (4) Do sample biases resulting from the proposed recruitment method influence travel behavior modeling? If so, how can we remedy them?

To address the questions raised above and bridge the gap in the literature regarding recruiting survey respondents from a preceding travel survey, we do the following:

(1) We analyze the two-stage self-selection/non-response biases simultaneously (i.e., willingness to participate in a follow-up survey and actual response behavior) for respondents *recruited from a previous travel survey* (the National Household Travel Survey, NHTS), using a probit with sample selection (PSS) model. We also propose several standardized PSS model performance measures to enable model comparisons (Chapter 5).

(2) We apply the PSS model to a holdout sample to decompose biases (e.g., dataset bias, self-selection bias, non-response bias) accumulated along the way and further analyze the representativeness of the recruited survey respondents by comparing sample and population marginal distributions for various variables. Furthermore, we apply the PSS model to predict follow-up survey samples from different geographic regions in the U.S. as another application example and to check the model's generalizability (Chapter 6).

(3) Using an internal-external validation procedure, we evaluate the necessity and the performance of applying two techniques (i.e., sample selection model and sample weights) to remedy the influence of sample biases on travel behavior models (i.e., vehicle-miles driven, VMD).

By understanding the dataset biases that can result when respondents are recruited from a preceding survey (e.g., NHTS), researchers/practitioners can better assess the tradeoff between data quality and resource constraints associated with respondent recruitment. Moreover, understanding these biases and the consequence of travel behavior modeling would allow survey developers to adjust their invited sample – for example, by oversampling underrepresented groups in the follow-up surveys. This work would, therefore, be particularly useful for transportation professionals if the NHTS retained the willingness question as a recurring item in future surveys, thereby allowing local agencies and researchers to recruit follow-up respondents from the NHTS sample efficiently. Even outside of the NHTS, the contributions of this thesis have general findings and implications for researchers using the approach of recruiting respondents from prior surveys.

CHAPTER 2. LITERATURE REIVEW

As mentioned, continuously declining survey response rates make it increasingly difficult for survey developers to obtain high-quality survey data with the same survey budgets as in the past. To enhance response rates, researchers and practitioners have developed and applied many approaches for aiding in the survey recruitment process.

We first summarize a few commonly used recruitment approaches and the accompanying sample biases. The use of survey incentives is an effective approach to increase survey response rates; examples of these include lotteries, tokens, and philanthropic donations (Edwards et al., 2002, Young et al., 2020). Coryn et al. (2020) found the lottery to be the most cost-effective incentive format, while Parsons and Manierre (2014) showed that unconditional incentives might exacerbate the overrepresentation of females among survey respondents. Using different survey modes (e.g., mail, phone, and web) is another way to increase response rates of specific population groups. For example, web surveys usually generate a much lower response rate than mail surveys in general (Manfreda et al., 2008, Hardigan et al., 2012), but younger generations such as college students are more responsive to web surveys (Shih and Xitao, 2008, Börkan, 2010). However, the sample may retain biases associated with the sampling mode, i.e., a mode effect. In a survey aimed at college students, Carini et al. (2003) found that web survey respondents gave more favorable responses regarding computing and information technology than the paper survey respondents. Survey developers could also obtain higher response rates by carefully selecting the sampling frame (Wolf et al., 2005). In recent years, scholars have used commercially-operated online opinion panels, consisting of people who pre-register for survey participation in return for rewards (e.g., cash, vouchers), to reach out to survey respondents and enhance response rates (Neufeld and Mokhtarian, 2012). Some companies that operate these online opinion panels allow quota sampling within the panelists to ensure a representative sample regarding the selected control variables (usually sociodemographic variables). Still, this does not guarantee the representativeness of other variables. For example, a recent study by this team found that online opinion panel respondents have significantly lower life satisfaction than respondents recruited from other sources, even when controlling for socio-demographics (Wang et al., 2020).

Another approach, as previously detailed in the Introduction, entails the recruitment of survey respondents who indicated willingness to respond in prior surveys (e.g., Lin et al., 2011). As with the other recruitment approaches discussed, this method also results in unrepresentative samples. Couper et al. (2007) modeled internet users' willingness to do an online survey and their subsequent follow-up response. They concluded that self-selected samples of internet users are not representative of the population with respect to demographic, financial, and health-related variables. In another example, Germany's Federal Statistical Office developed an access panel (a pool of persons willing to take part in voluntary surveys) from a large-scale household survey. The access panel was then used as the sampling frame for multiple surveys. Amarov and Rendtel (2013) explored the survey participation propensity of the access panel and identified self-selection biases existing in age, household size, and item-nonresponse. An accompanied simulation experiment (Tobias et al., 2013) on the selection process of the access panel emphasizes the importance of constructing proper statistical models for the access panel recruitment to ensure the appropriate usage of this high-response-rate and low-cost recruitment method. Similarly, Adriaan and Jacco (2009) applied bivariate logistic regressions to analyze the selectivity of the nonresponse of an online panel, which was recruited using a three-stage process: participation in a first telephone interview, willingness to be recontacted, and final agreement to participate in the online panel. The authors found selection biases with regards to age, income, and personal computer ownership.

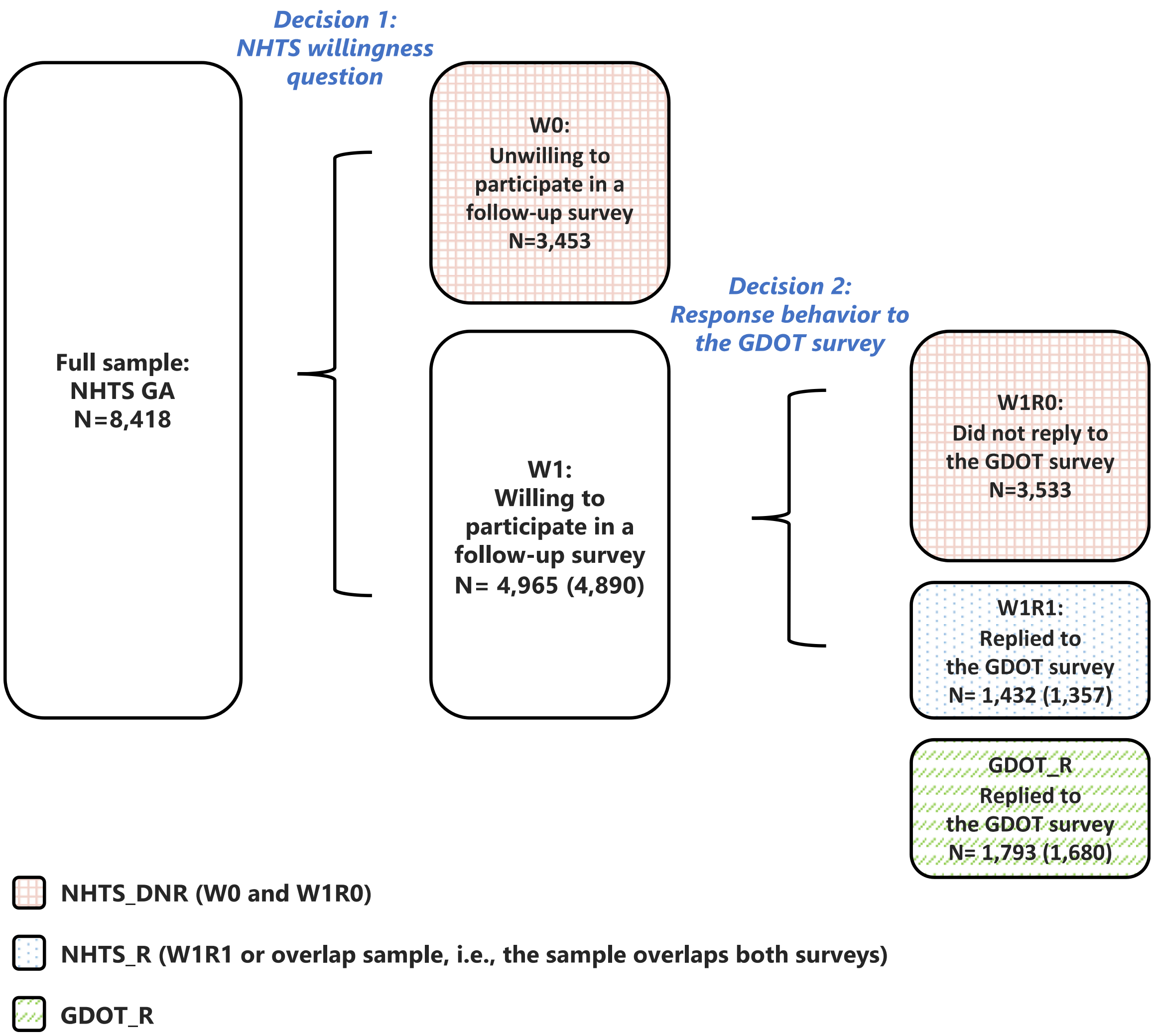
In the transportation domain, recruiting survey respondents from a preceding survey has not been widely adopted and/or examined. Although studies on the specific topic are limited, some transportation studies have examined the nonresponse bias in travel surveys, which could inform the analysis of self-selection biases in recruiting survey respondents from a preceding travel survey. Wittwer and Hubrich (2015) reached out to survey nonrespondents with an abbreviated survey, and found that age and household size have significant differences between main survey respondents and nonrespondents. de Haas et al. (2018) used information obtained from a screening survey and found that age, gender, and education influence people's willingness to participate in a household travel survey panel. They also found that willingness to participate in a travel survey could modify model coefficients and slightly improve the fits of mode choice models.

This study aims to address the literature gap by examining the practice of recruiting respondents from NHTS for a statewide travel survey, and constructing a proper statistical model for the recruitment process in the transportation context. We apply the probit with sample selection (PSS) model for the main analysis, which remedies the selection biases by allowing correlations between the unobservables in the selection and outcome equations (Heckman, Tobias, & Vytlacil, 2001). The PSS model was proposed by van de Ven and van Praag (1981), which is modified from the Heckman model (Heckman, 1976; originally designed for correcting sample selection biases in linear regressions, which will be used in Chapter 7) to fit binary outcome dependent variables. In the transportation domain, sample selection models have been applied for various purposes, one of the most common of which is to correct for residential self-selection effects (Cao, 2009; Chen, Wu, Chen, Zegras, & Wang, 2017; van Herick & Mokhtarian, 2020). In that context, outcomes are observed for both "selected" and "unselected" groups. In other contexts, including ours, outcomes are only observed for "selected" cases – for us, the cases who self-select into both being willing to respond, and actually responding, to a follow-up survey (Alemi, Circella, Mokhtarian, & Handy, 2019; Sun, Wang, & Wan, 2019).

CHAPTER 3. DATA DESCRIPTION

The National Household Travel Survey (NHTS) is a repeated cross-sectional travel survey conducted by the Federal Highway Administration, and is widely used by regional planning agencies across the United States. The Georgia subsample of the 2017 NHTS constitutes the main survey dataset used for this study. The NHTS typically obtains household, individual, vehicle, and trip information using several survey instruments; these include a recruitment survey, a retrieval survey, travel logs, and a vehicle odometer mileage form. In 2017, for the first time, NHTS allowed states to opt into including a question regarding respondents' willingness to participate in follow-up travel surveys, and Georgia was one of the six states/regions that chose to do so. We segmented NHTS Georgia respondents based on their willingness to participate in a follow-up survey as well as their actual response behavior to the follow-up survey (see *Decisions* in Figure 1). The follow-up survey, denoted the GDOT survey in Figure 1, is further discussed later in this section.

As shown in Figure 1, the first decision was made through the willingness question in the NHTS (i.e., "Would you be willing to participate in a follow-up survey?"). This question is *only* asked of the main household respondent (i.e., the respondent who answered household-related questions in the retrieval survey), and solely of those living in the regions (i.e., states or Metropolitan Planning Organization areas) that specifically requested the inclusion of this question, with Georgia being one of those regions as mentioned before. As such, we used only the main household respondents for analysis purposes, as we did not have additional information regarding other household members' willingness to participate in a follow-up survey. The final working dataset comprised 8,418 respondents, 4,965 of whom indicated a willingness to participate in a follow-up survey (W1), whereas the remaining 3,453 respondents did not want to be contacted again for future surveys (W0).



Note: numbers in parentheses are the sample sizes used in Chapter 7.

Figure 1 – Data sources and structure of analysis

For the 4,965 NHTS respondents who indicated a willingness to participate in a follow-up survey, their second decision (Figure 1) was made through their actual response to a follow-up survey, the Georgia Department of Transportation Emerging Technologies

Survey (GDOT survey, Kim et al., 2019). The GDOT survey is a 15-page attitudinally-rich travel survey with an emphasis on the impacts of emerging technologies on travel behavior. Our research team mailed the GDOT survey to the 4,965 NHTS respondents in September 2017. Ultimately, 1,432 of the 4,965 NHTS respondents replied to the GDOT survey (W1R1), while the remaining 3,533 did not reply (W1R0). Thus, at this point, we have segmented all 8,418 NHTS Georgia respondents based on the two decisions. Besides respondents recruited from the 2017 NHTS, the GDOT survey also recruited respondents through an address-based random sample, denoted as GDOT_R.

Table 1 presents descriptive statistics for each segment and the overall sample. Specifically, Table 1 (a) presents variables derived from the 2017 NHTS dataset, which will be mainly used in Chapters 5 and 6. Please note that we separate the working dataset (N=8,418) into a training set (60%, N=5,051) and a test set (40%, N=3,367) to enable appropriate model evaluation.

Table 1(b) presents variables derived from the GDOT survey, which will be used in Chapter 7. For the GDOT survey respondents (GDOT_R and NHTS_R), we conduct data cleaning based on the travel behavior variable *vehicle-miles driven (VMD) in the last week*. Specifically, we exclude cases with missing VMD and people who did not drive in the last week (zero VMD) from the final working sample.

As shown in Table 1(b), the two respondent groups have different population compositions, resulting from the different sampling frames (i.e., GDOT_R is an address-based random sample, while NHTS_R is composed of opt-in NHTS respondents). As such, we generate separate sample weights for GDOT_R and NHTS_R to make each group representative of the Georgia population regarding the selected weighting variables, including four household sociodemographic variables (i.e., residential location, household income, household size, and household vehicles) and five individual sociodemographic variables (i.e., sex, education, race, age, and work status). We could, instead, generate a set of sample weights for the whole GDOT sample first (i.e., combining GDOT_R and NHTS_R), and then rescale the sample weights within each group. However, we choose the former approach to correct for the different compositions between the two respondent groups more precisely. To generate the sample weights, we apply a combination of cell weighting and iterative proportional fitting (IPF) through an iterative process (see weighting details in Kim et al. (2019)).

Table 1 – Descriptive statistics of the working dataset (sample means/shares)

(a) NHTS variables

		Full sample: NHTS GA	**W0: Unwilling to be contacted**	**W1: Willing to be contacted**	**W1R0: Willing but did not reply**	**W1R1: Willing and did reply**
	Sample size	**8,418**	**3,453**	**4,965**	**3,533**	**1,432**
Household sociodemographic	Household size (persons)*	2.13	2.17	2.10	2.13	2.01
	Home ownership (yes)	0.75	0.80	0.71	0.66	0.84
Individual sociodemographic	Age*	55.56	57.30	54.35	52.46	59.00
	Has a medical condition (yes)	0.13	0.13	0.13	0.14	0.12
	Gender (female)	0.58	0.57	0.59	0.60	0.55
	Born in US (yes)	0.93	0.91	0.94	0.93	0.95
	Race: white (yes)	0.73	0.74	0.72	0.69	0.79
	Education†					
	Less than a high school graduate	0.038	0.043	0.035	0.041	0.022
	High school graduate or GED	0.19	0.20	0.17	0.18	0.15
	Some college or associates degree	0.30	0.29	0.30	0.30	0.30
	Bachelor's degree	0.24	0.23	0.24	0.24	0.26
	Graduate degree or professional degree	0.24	0.23	0.25	0.24	0.28
	Worker (yes)	0.54	0.52	0.56	0.59	0.48
Travel-related characteristics	No. of trips recorded in one-day travel diary *	3.90	3.52	4.16	4.03	4.47
	Transit usage frequency*1	0.64	0.40	0.81	0.95	0.46
Survey-related characteristics	Household income - missing value	0.035	0.064	0.015	0.016	0.011
	VMD - "I don't know"	0.25	0.32	0.20	0.21	0.17
	VMD - "I prefer not to answer"	0.015	0.025	0.009	0.009	0.008
Land use characteristics	Housing units per sq. mi.*	822.51	769.92	859.07	920.44	707.68

(b) GDOT variables

		NHTS_R		GDOT_R	
		Non-weighted	Weighted	Non-weighted	Weighted
	Sample size	**1,357**		**1,680**	
Travel behavior	Vehicle-miles driven (VMD) in the last week (mi) *	134.22	135.83	156.45	156.35
Attitudes[2]	Travel liking*	-0.05	-0.07	0.07	0.12
	Commute benefit*	0.00	0.04	-0.01	0.00
	Family-oriented*	0.01	-0.10	0.01	-0.14
	Car owning*	0.05	0.01	0.03	0.00
	Polychronic*	0.00	0.02	0.04	0.06
Sociodemographic	Race: white (yes)	0.82	0.67	0.79	0.63
	Gender (female)	0.55	0.51	0.42	0.51
	Worker (yes)	0.52	0.64	0.61	0.68
	Household income†				
	Less than $25,000	0.13	0.20	0.08	0.16
	$25,000 to $49,999	0.22	0.22	0.18	0.24
	$50,000 to $ 74,999	0.22	0.20	0.21	0.20
	$75,000 to $99,999	0.15	0.09	0.17	0.13
	$100,000 to $149,999	0.18	0.19	0.20	0.15
	$150,000 or more	0.11	0.10	0.16	0.13
	No. of household vehicles†				
	1	0.31	0.36	0.24	0.35
	2	0.39	0.34	0.41	0.33
	3	0.19	0.17	0.21	0.17
	4+	0.10	0.09	0.13	0.11
Land use characteristics	Rural area	0.13	0.22	0.01	0.03

Notes: [1] 0=Never; 1=Less than once a month; 2=1-3 times a month; 3=1-2 times a week; 4=3-4 times a week; 5=5 or more times a week.
[2] Factor scores. Factor scores are no longer fully standardized after data cleaning.
* Treated as continuous variables for modeling; descriptive statistics are sample means. † Treated as continuous variables for modeling; descriptive statistics are sample shares. The remaining variables are binary variables.

CHAPTER 4. METHODOLOGY

4.1 PSS Model Structure and Application

In this thesis, we model and analyze two consecutive decisions made by the 2017 NHTS Georgia respondents: (1) their willingness to participate in a follow-up survey and (2) their actual response behavior to the follow-up survey. The perspective we take in Chapters 4 and 5 is that the target behavior of interest is the participation in the second survey (by anyone), and the goal is to obtain consistent estimates of the coefficients of the explanatory variables in the model predicting that behavior. But since we are only able to observe the second decision for NHTS respondents who are willing to participate in a follow-up survey (i.e., respondents who are self-selected, and so received a follow-up survey), modeling the observed response behavior only of this subsample could produce biased (econometrically inconsistent) estimates of those coefficients, relative to their true values in the population at large.

To address the self-selection bias, Heckman (1976) proposed the sample selection model as a corrective method for linear regression models. Given the binary nature of the two decisions in our case (i.e., willing/unwilling to participate, respond/do not respond to the follow-up survey), we apply the analogous corrective method for discrete choice models, the probit with sample selection (PSS) model (van de Ven and van Praag, 1981), to deal with the self-selection bias.

In the PSS model, we have a selection model and an outcome model, which correspond to the willingness and response decisions, respectively. The selection and outcome models are defined as

$$y_i^{S^*} = \boldsymbol{z_i}\boldsymbol{\gamma} + \varepsilon_i^s, \tag{1}$$

$$y_i^{O^*} = \boldsymbol{x_i}\boldsymbol{\beta} + \varepsilon_i^O, \tag{2}$$

$$y_i^S = \begin{cases} 0, & if\ y_i^{S^*} < 0 \\ 1, & otherwise \end{cases} \tag{3}$$

$$y_i^O = \begin{cases} unobserved, & if\ y_i^S = 0 \\ 0, & if\ y_i^S = 1\ and\ y_i^{O^*} < 0 \\ 1, & if\ y_i^S = 1\ and\ y_i^{O^*} \geq 0, \end{cases} \tag{4}$$

where $y_i^{S^*}$ is the continuous latent variable indicating the tendency for individual i to be *willing* to participate in a follow-up survey; $y_i^{O^*}$ is the tendency for individual i to *respond* to the follow-up survey (the GDOT survey); $\boldsymbol{z_i}$ and $\boldsymbol{x_i}$ are vectors of explanatory variables for the selection and outcome models, respectively; $\boldsymbol{\gamma}$ and $\boldsymbol{\beta}$ are the corresponding coefficient vectors; and ε_i^s and ε_i^O are error terms that capture the unobserved effects in the two models. As is standard, we assume that the error terms follow a bivariate normal distribution:

$$\begin{pmatrix} \varepsilon^S \\ \varepsilon^O \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right). \tag{5}$$

In the observed choice formulations (Eqs. 3-4), y_i^S is the observed binary selection choice (willing to participate in a follow-up survey = 1, unwilling = 0), and y_i^O is the observed binary outcome choice (responds to the follow-up survey = 1, does not respond = 0). We observe the outcome if and only if the latent selection variable $y_i^{S^*}$ is positive (or y_i^S=1). Finally, we estimate the parameters $\widehat{\boldsymbol{\gamma}}, \widehat{\boldsymbol{\beta}}, \hat{\rho}$ using maximum likelihood estimation. The log-likelihood can be written as

$$\ell(\widehat{\boldsymbol{\gamma}}, \widehat{\boldsymbol{\beta}}, \hat{\rho}) = \sum_{i:y_i^S=0} \log\left(\Phi(-\boldsymbol{z_i}\widehat{\boldsymbol{\gamma}})\right) + \sum_{\substack{i:y_i^S=1,\\ y_i^O=1}} \log\left(\Phi_2\left(\boldsymbol{z_i}\widehat{\boldsymbol{\gamma}}, \boldsymbol{x_i}\widehat{\boldsymbol{\beta}}; \hat{\rho}\right)\right) + \sum_{\substack{i:y_i^S=1,\\ y_i^O=0}} \log\left(\Phi_2\left(\boldsymbol{z_i}\widehat{\boldsymbol{\gamma}}, -\boldsymbol{x_i}\widehat{\boldsymbol{\beta}}; \hat{\rho}\right)\right), \tag{6}$$

where $\Phi\ (\cdot)$ represents the cumulative univariate standard normal distribution function and $\Phi_2(\cdot)$ represents the cumulative bivariate normal distribution function. With this model formulation, we can calculate three sets of probabilities: the marginal probabilities of being willing or not (Eqs. 7-8), joint probabilities of being willing and responding or not responding (Eqs. 9-10), and conditional probabilities of responding or not, given willingness (Eqs. 11-12).

Marginal probabilities:

$$P\left(y_i^S = 0\right) = \Phi(-\boldsymbol{z_i}\widehat{\boldsymbol{\gamma}}) \tag{7}$$

$$P\left(y_i^S = 1\right) = \Phi(\boldsymbol{z_i}\widehat{\boldsymbol{\gamma}}) \tag{8}$$

Joint probabilities:

$$P(y_i^S = 1, y_i^O = 0) = \Phi_2(\boldsymbol{z_i}\widehat{\boldsymbol{\gamma}}, -\boldsymbol{x_i}\widehat{\boldsymbol{\beta}}; \hat{\rho}) \tag{9}$$

$$P(y_i^S = 1, y_i^O = 1) = \Phi_2(\boldsymbol{z_i}\widehat{\boldsymbol{\gamma}}, \boldsymbol{x_i}\widehat{\boldsymbol{\beta}}; \hat{\rho}) \tag{10}$$

Conditional probabilities:

$$P(\, y_i^O = 0 \mid y_i^S = 1) = \Phi_2(\boldsymbol{z_i}\widehat{\boldsymbol{\gamma}}, -\boldsymbol{x_i}\widehat{\boldsymbol{\beta}}; \hat{\rho})/\Phi(\boldsymbol{z_i}\widehat{\boldsymbol{\gamma}}) \tag{11}$$

$$P(\, y_i^O = 1 \mid y_i^S = 1) = \Phi_2(\boldsymbol{z_i}\widehat{\boldsymbol{\gamma}}, \boldsymbol{x_i}\widehat{\boldsymbol{\beta}}; \hat{\rho})/\Phi(\boldsymbol{z_i}\widehat{\boldsymbol{\gamma}}) \tag{12}$$

The three sets of probabilities reflect distinct statistical explanations, which should be appropriately used under different model applications. In Table 2, we summarize a few application scenarios and the corresponding probabilities, in the context of a two-stage survey sample recruitment. This study will mainly focus on the first application scenario (Section 6.1) while lightly touching on the third one in Section 6.2. It is worth mentioning here that, similar to any other models, prediction errors exist in the PSS model applications. We summarize several model performance measures in the next section to help evaluate the quality of the model.

Table 2 – Applications of the PSS model in different scenarios

Scenario	Model and probability used in the *prediction*
1. Decomposition of the deviation (i.e., bias) of the follow-up survey sample from the population into its various components (e.g., dataset bias, self-selection bias, prediction errors). This is enabled by comparisons of the predicted sample and population distributions at various stages of the model.	• Use the selection model and the marginal probability of selection $P(y_i^S = 1)$ for the prediction of people who are willing to participate in a follow-up survey. • Use the joint model and joint probability of selection and outcome $P(y_i^S = 1, y_i^O = 1)$ for the final prediction of follow-up survey respondents.
2. Prediction of the response to a second-stage survey following a large-scale first-stage survey (e.g., NHTS) that contains the willingness question. Survey developers conduct a small-scale field test of the second-stage survey to enable the estimation of the PSS model, and then apply the *outcome model* to the remainder of the willing first-stage sample to predict the size and characteristics of the full-scale second-stage sample.	• Use the conditional probability $P(y_i^O = 1 \mid y_i^S = 1)$ to predict the second-stage response of the willing first-stage sample.
3. Prediction of the response to a second-stage survey following a large-scale first-stage survey (e.g., NHTS) that does not contain the willingness question. Survey developers do not know the response willingness of the first-stage sample and adopt a PSS model estimated from other datasets/ regions to predict the size and characteristics of the second-stage sample.	• Using a joint model estimated from other datasets, compute the joint probability $P(y_i^S = 1, y_i^O = 1)$ to predict the second-stage response from the full first-stage sample.

4.2 PSS Model Performance Measures

Due to the two-level model structure of the PSS model, the usual discrete choice model performance measures cannot be directly applied, which might explain why PSS models have diverse performance measures in the literature. Accordingly, we aim to address the lack of clarity in the literature surrounding PSS measures by providing a resource for six frequently used categories of model measures, adjusted based on the PSS model structure: the log-likelihood, McFadden's pseudo-R^2, information criteria, correlation, root mean squared error, and success table. Table 3 provides definitions of the six measures, and gives examples of them being applied within the literature. We also demonstrate their use by calculating all of them for the PSS model developed in this thesis in Section 5.2.

Since both selection and outcome models are binary probit models, we first introduce three log-likelihoods associated with the PSS model: equally-likely (EL) model, market-share (MS) model, and full model (Eqs. 13-15). Log-likelihoods provide direct measures of the model performance, but they do not allow model comparisons across studies since the values are related to the sample size. McFadden's pseudo-R^2 (ρ^2) provides a measure that is derived from the log-likelihoods but is bounded between 0 and 1. A higher ρ^2 means greater information explained by the model (Mokhtarian, 2016). Eqs. 16 and 17 are ρ^2s with EL and MS bases, respectively. Information criteria such as the Akaike information criterion (AIC, Eq. 18) and Bayesian information criterion (BIC, Eq. 19) are also based on log-likelihoods. These criteria penalize the number of model coefficients to promote parsimony, which could be used for model selection. However, similar to the drawback of log-likelihoods, we do not have a benchmark for such information criteria. The three log-likelihood-associated categories of measures are suitable when the overall PSS model performance is required, such as for Scenarios 1 and 3 in Table 2.

Another model performance measure is the correlation coefficient between predicted probabilities and observed choices. Since the observed choice is a binary variable and the predicted probability is a continuous variable, we apply point-biserial correlation coefficients (Eq. 20), which range between -1 (the wrong outcome is predicted with certainty) and 1 (the correct outcome is predicted with certainty). The closer r_{pb} is to 1, the better the model. Root mean squared error (RMSE) measures the discrepancy between the observed choice (0 or 1) and the predicted probability (Eq. 21). For our model, RMSE ranges from between 0 and 1, with smaller RMSE indicating better prediction results. Although the correlation and RMSE measures do not provide an overall measure of the PSS model but only measure separate model performances of the selection and outcome models, they are instrumental under specific application scenarios. For example, in the bias decomposition application (Scenario 1 in Table 2), separate performance measures provide comparable prediction error indicators between selection and outcome models as we decompose biases step by step (see Section 6.1 for more details). Separate model performance measures are also useful when we only need the performance of a single model (e.g., the outcome model performance with known selection results, Scenario 2 in Table 2).

The last model performance measure category is the probability-based success table, which was originally proposed by McFadden (2000). Given the two-level model structure of the PSS model, we could generate a 3×3 matrix based on the observation and model prediction results ($y_i^S = 0; y_i^S = 1, y_i^O = 0; y_i^S = 1, y_i^O = 1$). Eq. 22 calculates the number of cases in the mn^{th} cell in a success table. Success tables allow both overall model performance measures (i.e., overall prediction accuracy) and alternative-specific measures (i.e., success proportion, success index). Success tables are usually computed for both training and test sets to examine the generalizability of the model.

Table 3 – Model performance measures for probit with sample selection models

Measure	Formula	Eq.	PSS examples
Log-likelihood	$\ell(0) = \sum_{i:y_i^s=0} ln\left(\frac{1}{2}\right) + \sum_{\substack{i:y_i^s=1,\\ y_i^o=1}} ln\left(\frac{1}{2}\times\frac{1}{2}\right) + \sum_{\substack{i:y_i^s=1,\\ y_i^o=0}} ln\left(\frac{1}{2}\times\frac{1}{2}\right)$ $= -N_{y_i^s=0}\, ln\, 2 - \left(N_{y_i^s=1,y_i^o=1} + N_{y_i^s=1,y_i^o=0}\right) ln\, 4$	(13)	Ruiz and Habib (2016), Stavropoulou (2011)
	$\ell(c) = \sum_{i:y_i^s=0} ln\left(\frac{N_{y_i^s=0}}{N}\right) + \sum_{\substack{i:y_i^s=1,\\ y_i^o=1}} ln\left(\frac{N_{y_i^s=1,y_i^o=1}}{N}\right) + \sum_{\substack{i:y_i^s=1,\\ y_i^o=0}} ln\left(\frac{N_{y_i^s=1,y_i^o=1}}{N}\right)$ $= N_{y_i^s=0}\, ln\, N_{y_i^s=0} + N_{y_i^s=1,y_i^o=1}\, ln\, N_{y_i^s=1,y_i^o=1} + N_{y_i^s=1,y_i^o=0}\, ln\, N_{y_i^s=1,y_i^o=0} - N\, ln\, N$	(14)	
	$\ell(\hat{\gamma},\hat{\beta},\hat{\rho}) = \sum_{i:y_i^s=0} log\ (\Phi(-z_i\hat{\gamma})) + \sum_{\substack{i:y_i^s=1,\\ y_i^o=1}} log\ (\Phi_2(z_i\hat{\gamma}, x_i\hat{\beta}; \hat{\rho})) + \sum_{\substack{i:y_i^s=1,\\ y_i^o=0}} log\ (\Phi_2(z_i\hat{\gamma}, -x_i\hat{\beta}; \hat{\rho}))$	(15)	
McFadden's pseudo-R[2] **[1]**	$\rho_{EL}^2 = 1 - \frac{\ell(\hat{\gamma},\hat{\beta},\hat{\rho})}{\ell(0)}$	(16)	Drucker and Khattak (2000)
	$\rho_{MS}^2 = 1 - \frac{\ell(\hat{\gamma},\hat{\beta},\hat{\rho})}{\ell(c)}$	(17)	
Information criteria	$AIC = 2k - 2\ell(\hat{\gamma},\hat{\beta},\hat{\rho})$	(18)	Alemi et al. (2019)
	$BIC = ln(N)\, k - 2\ell(\hat{\gamma},\hat{\beta},\hat{\rho})$	(19)	
Point-biserial correlation coefficient	$r_{pb} = \frac{m_1 - m_0}{s}\sqrt{\frac{n_1 n_0}{n^2}}$ where m_1 and m_0 are the average probabilities for the binary alternatives; s is the standard deviation of the probabilities for all cases; n_1 and n_0 are the number of cases for each alternative; n is the sum of n_1 and n_0.	(20)	Van de Ven and Van Praag (1981) (similar idea)

	Selection models use the marginal probability to calculate m_1 and m_0 with the full dataset. Outcome models use the conditional probability to calculate m_1 and m_0 with observed selected samples only.		
Root mean square error (RMSE)	$$RMSE = \sqrt{\frac{\sum_i (y_i - \hat{p}_i)^2}{n}}$$ where y_i is the observed choice; $\hat{p}_i$ is the predicted probability of that choice (uses marginal probability for the selection model, and conditional probability for the outcome model); n is the number of cases.	(21)	-
Success table	$$N_{ab} = \sum_i I_i^a \hat{p}_i^b$$ where N_{ab} is the expected number of cases whose observed choice is a and predicted choice is b; I_i^a is an indicator function which equals 1 when the observed choice of case i corresponds to a, and equals 0 otherwise; and $\hat{p}_i^b$ is the predicted probability for case i to choose b.	(22)	-

[1] Note that in this case, "equally likely" means that the two alternatives for each of the two models are equally likely, not that the three possible final combinations ($y_i^s = 0;\ y_i^s = 1, y_i^o = 1; and\ y_i^s = 1, y_i^o = 0$) are equally likely. That is, the respective probabilities for those three events are 1/2, 1/4, 1/4, not 1/3, 1/3, 1/3.

CHAPTER 5. PSS MODEL RESULTS

In this chapter, we first present the PSS model result and then measure the model performance with six metrics presented in the previous chapter.

5.1 Model Results

5.1.1 Selection Model

The selection model explains respondents' willingness to participate in a follow-up survey. We organized the explanatory variables into three categories: household- and individual-level sociodemographic characteristics, travel-related characteristics, and survey-related characteristics (Table 4).

Among the household-level sociodemographic characteristics tested, we see that respondents from larger households are less willing to participate in a follow-up survey compared to respondents from smaller households (see similar findings in Amarov and Rendtel (2013)); we propose that one reason for this finding may reside in the format of the NHTS. Specifically, NHTS requires all household members five years of age or older to complete the personal section in the retrieval survey and record their travel on the designated travel day. As such, it is more time-consuming and burdensome for larger households to complete the NHTS requirements, which may weaken the motivation of the main household respondent to volunteer for another survey. Furthermore, the log transformation of household size indicates that the impact on survey willingness of a one-person increase in household size becomes weaker (but still negative) as the household size grows. The model also shows that homeowners are less willing to participate in a follow-up survey, perhaps because of the greater time consumed by the responsibilities of homeownership.

Among individual-level sociodemographic characteristics, we find that younger people, women, and people who were born in the U.S. are more willing to participate in a follow-up survey. We also find that individuals who have a medical condition restricting them from traveling outside the home are more willing to participate than people who do not have such restrictions. On the one hand, the travel-limited group comprises primarily older individuals who may be retired and thus have more time for doing surveys. The results may also reflect the altruism of the travel-limited group, possibly suggesting that they seek to contribute to society in ways that are accessible to them. On the other hand, their interest and participation in travel-related surveys may also highlight the unmet travel demands of these individuals.

Among travel-related characteristics tested, the model shows that people who report more trips on the designated travel day are more willing to participate in a follow-up survey, which runs counter to our expectations. Based on the findings regarding household size, we concluded that having to record more trips would reduce the willingness to participate in a follow-up survey. A resolution of the paradox might reside in the travel-liking attitude. Specifically, travel-liking people might record their travel logs more comprehensively (e.g., walk one block to buy coffee in the middle of the workday, pick up laundry on the way back home), and also be eager to complete a future travel survey[1]. In

[1] Since the NHTS did not collect respondents' attitudes towards travel-liking, we could not test our hypothesis with the presented PSS model. However, to investigate this conjecture we constructed a binary probit model for respondents' willingness to participate in a follow-up survey using the GDOT survey data, which collected respondents' willingness to participate in yet another follow-up survey as well as the travel-liking

contrast, those reporting fewer trips might tend to ignore trivial, non-mandatory, short trips or stops because they are not sensitive enough to catch these trips and/or they want to alleviate the burden of completing the travel logs. Moreover, frequent transit users are also more willing to participate in a follow-up survey, which might be due to their desire to improve the quality of their travel experience by providing feedback through travel surveys.

Survey-related characteristics constitute a group of variables unique to the selection model: item non-responses. In NHTS, many questions provide choices of "I don't know" and "I prefer not to answer", which allows respondents to protect their privacy for sensitive information (e.g., income) and avoid imprecise estimations (e.g., vehicle-miles driven, VMD). In our model, we combine "I don't know" and "I prefer not to answer" for the household income question and treat both of these responses as indicative of respondents who choose to protect their privacy. The resultant variable is called the household income missing value indicator, and the negative sign of the coefficient implies that respondents who are more protective of their privacy are less willing to participate in a follow-up survey[2]. Similarly, a previous study (Amarov and Rendtel, 2013) also found that item-nonresponse in a preceding survey strongly indicates the reluctance to participate in follow-up surveys. Regarding VMD, since the variable is self-estimated by NHTS respondents, we believe some respondents who do not care much about their travel might be unclear about their annual VMD. As such, "I don't know" may represent an apathetic attitude

attitude. Results indicated that the travel-liking attitude positively associated with the willingness to participate at a significance level (p-value) of 0.001.

[2] When we treat the two responses ("I don't know" and "I prefer not to answer") as separate variables, their coefficients are very similar.

toward travel, whereas “I prefer not to answer” reflects a privacy-protective attitude, and accordingly we keep those responses separate for VMD. The model shows that both respondents who are less interested in their travel behavior and respondents who are protective of their privacy regarding travel behavior, are less willing to respond to a follow-up survey.

5.1.2 Outcome Model

The outcome model explains the actual, observed response to the GDOT survey for NHTS respondents who reported being willing to participate in a follow-up survey. The outcome model contains two groups of explanatory variables: household- and individual-level sociodemographic characteristics, and land use characteristics.

Homeownership is the household-level sociodemographic characteristic that was found to be significant in both the selection and outcome models. Interestingly, however, the variable has opposing signs in the two models. Specifically, homeowners were less willing to participate in a follow-up survey than the renters, but among respondents who *are* willing to participate in a follow-up survey, homeowners are *more* likely to respond than renters. One reason for the latter outcome may be that homeowners are more likely to receive the follow-up survey because they move less often, whereas the follow-up survey might not reach renters due to address changes. Another reason might be that homeowners were initially less willing to commit their time to a follow-up survey due to having more household responsibilities, but once opting in, the same commitment to one’s responsibilities makes them more likely to follow through.

Age and medical conditions are individual-level sociodemographic characteristics that are significant in both selection and outcome models, albeit also with opposing signs. In general, younger people report being more willing to participate in a follow-up survey compared to older people, while among respondents expressing willingness to participate in a follow-up survey, older people are more likely to actually respond than younger people. Potentially, younger people are less reachable (i.e., more transient) or less able to participate when the time actually comes, even though they may aspire to be helpful. However, previous studies (Adriaan and Jacco, 2009; Amarov and Rendtel, 2013) found that households with older people are less likely to participate in follow-up surveys, which might be an outcome confounded with poor health conditions. In particular, we find that medically-restricted respondents are less likely actually to respond to a follow-up survey after expressing the willingness to do so than people who do not have any travel restrictions, even though they were more likely to indicate being willing to do so in the first place compared to the no-restriction group. It is possible that the medical conditions that restrict travel might also limit these respondents from completing the follow-up survey (e.g., poor eyesight); it is also possible that the medical conditions worsened during the approximately one-year interval between surveys. The outcome model also shows that white, higher-educated people are more likely to respond to the follow-up survey, while workers are less likely to respond to the follow-up survey than non-workers, probably due to time constraints on the part of the worker group.

The land use characteristics are the variable group unique to the outcome model, as they were only found to be significant in this model. We find that people from less dense areas are more likely to respond to the follow-up survey, which could be related to the types of individuals who typically live in lower density areas in Georgia (e.g. older, more likely to be retired)[3].

5.1.3 Error Terms

The correlation of the error terms in the selection and outcome models is highly significant and sizable (-0.574), which indicates that the self-selection bias (expressed willingness to participate in a follow-up survey) significantly influences whether or not an individual responds to a follow-up survey. Specifically, its negative value signifies that on net, unobserved characteristics that *increase* the reported willingness to participate in a follow-up survey will tend to *decrease* the tendency to actually do so. Or conversely, unobserved factors that decrease the reported willingness (e.g., more time demands) might be the same factors that influence respondents to keep the commitment once they opt in to the follow-up survey. Among other reasons, this might arise from the three explanatory variables that have opposing signs in the selection and outcome models (i.e., homeownership, age, and medical condition): since the respective error terms are equal to the observed outcome minus the contribution of the observed explanatory variables, a higher value of any of those three variables will (increase the subtracted contribution and hence) decrease the error term for one equation while (conversely) increasing it for the other. Having already seen this pattern from the three *observed* explanatory variables with opposing signs in the selection and outcome models (i.e., homeownership, age, and medical condition), it is not hard to imagine that it could prevail among *unobserved* variables as well.

[3] We checked the correlations of housing density with the home ownership (-0.18), household size (-0.11), age (-0.13), and worker (0.077) variables, but none of them were large enough to cause collinearity concerns.

Table 4 – Probit with sample selection model results (N=5,051)

Variables	Coefficient	Std. Error
Selection model: willingness to participate in a follow-up survey		
Household sociodemographic		
Household size (natural log-transformed)	-0.185***	0.0377
Homeowner	-0.178***	0.0469
Individual sociodemographic		
Age	-0.00726***	0.00139
Has a medical condition	0.150*	0.0581
Female	0.111**	0.0369
Born in US	0.194**	0.0694
Travel-related characteristics		
No. of trips on diary day	0.0478***	0.00629
Transit usage frequency	0.0579*	0.0230
Survey-related characteristics		
Household income - missing	-0.857***	0.106
VMD - "I don't know"	-0.464***	0.0424
VMD - "I prefer not to answer"	-0.796***	0.140
Constant	0.188*	0.0852
Outcome model: response to the follow-up survey		
Household sociodemographic		
Homeowner	0.417***	0.0606
Individual sociodemographic		
Age	0.0120***	0.00178
Has a medical condition	-0.331***	0.0733
Race: white	0.106*	0.0534
Education	0.0746***	0.0215
Worker	-0.181***	0.0540
Land use characteristics		
Housing units per sq. mi.	-0.0528*	0.0246
Constant	-0.619***	0.129
Error terms correlation		
ρ	-0.574***	0.0964

*** Coefficient is statistically significant at the 0.001 level.
** Coefficient is statistically significant at the 0.01 level.
* Coefficient is statistically significant at the 0.05 level.
Note: Insignificant variables removed from the model include no. of vehicles per driver in the household, no. of children in the household, frequency of walk trips, and usage of delivery services, among others.

5.2 Model Performance Measure

In this section, we apply model performance measures from the six categories proposed in Section 4.2 to our PSS model. Table 5 presents measures from the first five categories including log-likelihood, McFadden's pseudo-R^2, information criteria, correlation, and root mean squared error. The success table is presented in Table 6.

As discussed previously, we cannot compare log-likelihoods and information criteria with models in other studies due to the varying sample sizes, whereas McFadden's pseudo-R^2s are comparable given their 0 to 1 range. In this study, McFadden's pseudo-R^2 are relatively low, which could result from the nature of predicting survey participation. The willingness to participate in a follow-up survey and the actual response also depend on people's mood and time pressure at the moment, and thus are hard to model. In the literature, the model fits regarding survey willingness and actual response are similar to ours. For example, Wittwer and Hubrich (2015) developed a binary logistic regression model of survey response behaviors and McFadden's pseudo-R^2 was 0.052 (relative to the constant-only model benchmark). Regarding an internet survey, Couper et al. (2007) obtained Cox and Snell pseudo-R^2s of 0.044 and 0.067 for the willingness and response models, respectively[4].

[4] To enable the comparison between our PSS model to the two single models in Couper et al. (2007), we calculate the Cox and Snell pseudo-R^2 with the formula $1 - \left(\frac{L(\boldsymbol{c})}{L(\widehat{\boldsymbol{\gamma}},\widehat{\boldsymbol{\beta}},\widehat{\rho})}\right)^{2/N}$, and the value is 0.115.

Table 5 – Probit with sample selection model measures (N=5,051)

Measure	Formula	Value
Log-likelihood	$\ell(\mathbf{0})$	-5571.517
	$\ell(\boldsymbol{c})$	-5231.426
	$\ell(\hat{\boldsymbol{\gamma}}, \hat{\boldsymbol{\beta}}, \hat{\rho})$	-4921.783
McFadden's pseudo-R^2	ρ_{EL}^2	0.117
	ρ_{MS}^2	0.059
Information criteria	AIC	9885.567
	BIC	10022.640
Point-biserial correlation coefficient	r_{pb}	r_{pb}(selection model) = 0.274
		r_{pb}(outcome model) = 0.271
Root mean square error (RMSE)	$RMSE$	$RMSE$ (selection model) = 0.473
		$RMSE$ (outcome model) = 0.439

The last model performance measure is the probability-based success table. As shown in Table 6, the bolded numbers on the diagonal represent the number of correct predictions, while the off-diagonal elements are the number of misclassifications. Based on the success table, we calculate overall prediction accuracy (sum of the diagonal elements divided by the total, which is 0.41 for the training set) and the alternative-specific accuracy (i.e., success proportion). Specifically, a *success proportion* is the number of correct predictions of a specific choice divided by the total number of predictions of that choice. For example, 45% of the people who are predicted to be unwilling to participate in a follow-up survey (y_i^S=0) actually do not want to participate in a follow-up survey. We could further normalize success proportions by the corresponding observed shares to receive *success indices*, which directly compare the performance of the calibrated model with the market-share prediction for each alternative. In general, we expect the success index to be greater than 1, signifying superiority of the final model over the market-share model. Larger success indices indicate more accurate predictions. For example, our model is respectively 1.11, 1.10, and 1.21 times better than the market-share model in predicting the three outcomes. Table 6(b) is the success table based on the test set. Recall that we separated the final working dataset (N=8,418) into a training set (60%, N=5,051) and a test set (40%, N=3,367) to enable appropriate model evaluation. In general, the PSS model has quite similar performances in the training and test sets, which indicates good generalizability of the model to “new” data drawn from the same context.

Table 6 – Success table

(a) Training set

	Pred. (y_i^S=0)	**Pred.** (y_i^S=1, y_i^O=0)	**Pred.** (y_i^S=1, y_i^O=1)	**Row total**	**Obs. share**
Obs. (y_i^S=0)	**935.16**	787.90	340.94	2064	0.41
Obs. (y_i^S=1, y_i^O=0)	787.89	**957.84**	356.27	2102	0.42
Obs. (y_i^S=1, y_i^O=1)	340.99	355.92	**188.10**	885	0.18
Column total	2064.04	2101.66	885.31	5051	
Pred. share	0.41	0.42	0.18		
Success prop.	0.45	0.46	0.21		**Acc.= 0.41**
Success index	1.11	1.10	1.21		

(b) Test set

	Pred. (y_i^S=0)	**Pred.** (y_i^S=1, y_i^O=0)	**Pred.** (y_i^S=1, y_i^O=1)	**Row total**	**Obs. share**
Obs. (y_i^S=0)	**630.51**	531.05	227.44	1389	0.41
Obs. (y_i^S=1, y_i^O=0)	536.72	**652.80**	241.47	1431	0.43
Obs. (y_i^S=1, y_i^O=1)	216.26	216.85	**113.89**	547	0.16
Column total	1383.49	1400.70	582.80	3367	
Pred. share	0.41	0.42	0.17		
Success prop.	0.46	0.47	0.20		**Acc.= 0.41**
Success index	1.10	1.10	1.20		

Note: Calculations contain rounding errors.

CHAPTER 6. PSS MODEL VALIDATION AND APPLICATION

In this chapter, we will first apply the PSS model to the hold-out NHTS Georgia sample (the test set) to further validate our model results (Parady, Ory, & Walker, 2021) and retrieve sample biases in the follow-up survey from multiple sources (Scenario 1, Table 2). We will then apply the PSS model to selected states in diverse geographic regions of the US (west to east: California, Minnesota, North Carolina, New York and Massachusetts) and the full 2017 NHTS national sample, to predict follow-up survey participation and test the transferability of the PSS model (Scenario 3, Table 2).

6.1 Inside Georgia: Breakdown of Sample Biases

In this section, we apply the PSS model to the test set to predict respondent participation in the follow-up survey, and compare the marginal distributions of several selected variables with the corresponding population[5] distributions derived from the 2018 American Community Survey five-year estimates (https://www.census.gov/programs-surveys/acs). By analyzing the distribution divergence between the follow-up survey respondents and the population, we summarize the potential biases residing in the sampling method, i.e., recruiting respondents from a preceding travel survey. Figure 2 visualizes the five bias sources: dataset bias, household representative bias, self-selection bias, non-response bias, and prediction error. Please see Table 7 for detailed distributions.

[5] Although we refer to these as "population" distributions for convenience and because they presumably closely approximate the true distributions, they are in fact based on samples, and accordingly the data has been weighted by the U.S. Census Bureau to correct for sampling and other biases.

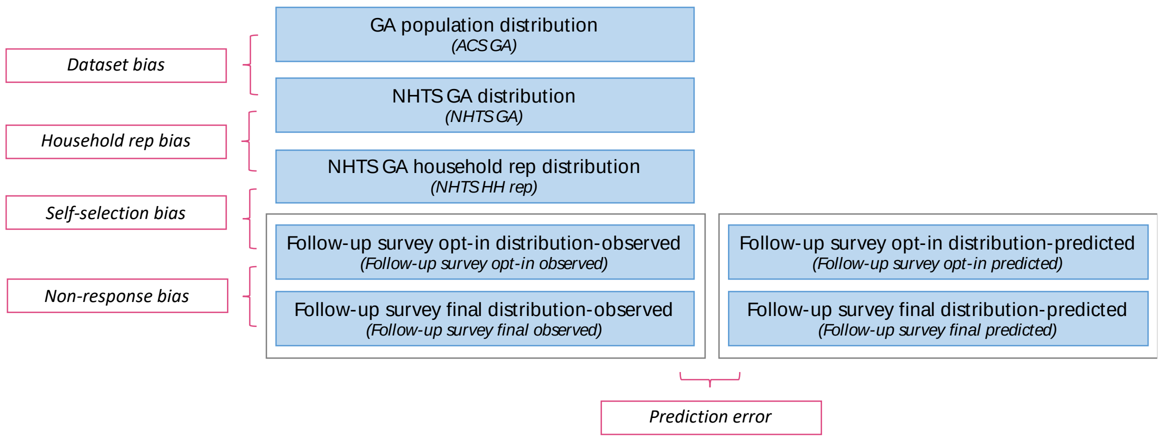


Figure 2 – Distribution bias breakdown

The PSS model has demonstrated the existence of self-selection biases through the highly significant and sizable correlation between the error terms in the selection and outcome models. Self-selection bias, however, is not the only source that contributes to the marginal distribution divergence between the follow-up survey respondents and the population (i.e., the bias in the follow-up survey respondents). As shown in Figure 2, the first contribution arises from any coverage, sampling, and non-response biases associated with the dataset of the preceding survey, which is the 2017 NHTS in our case. Since the 2017 NHTS creates individual and household weights using the 2015 ACS data as control variables, the dataset bias associated with those control variables is trivial (columns 1 and 2 in Table 7).

The second contribution to bias comes from the fact that only people who answer the household-related questions in the retrieval survey – i.e., "household representatives (reps)" – are asked the willingness question in the NHTS. The follow-up survey (i.e., the GDOT survey) was therefore delivered only to household representatives and not to any other household members. The household representative filter results in individual-level biases (e.g., age, gender). The household-level variables are not influenced since household weights are the same across household members. Consequently, the marginal distributions of individual-level variables have sizable differences between the 2017 NHTS Georgia sample and the household representative sample (columns 2 and 3 in Table 7). If the household representative filter could be removed (i.e., if the willingness question were asked of all NHTS respondents), we would expect a more representative follow-up survey sample (see Appendix A for details of a scenario that simulates this hypothetical situation, with results that support the conjecture).

The distribution divergence between NHTS household representatives and individuals who are willing to participate in a follow-up survey (opt-in) reflects the self-selection bias (columns 3 and 4 in Table 7). The distribution divergence between the opt-in individuals and individuals who actually complete the follow-up survey reflects a non-response bias (columns 4 and 6), which might result from multiple reasons, such as the opt-in individual being no longer willing or able to do the follow-up survey at the time when it was received, or the follow-up survey not reaching the opt-in individual due to an address change.

The distribution divergence between the observed follow-up survey final respondents and the corresponding PSS predicted results indicates the prediction error (columns 4 versus 5 and columns 6 versus 7 in Table 7).

Table 7 – Marginal distributions of selected variables

(a) Individual-level

Column number	1	2	3	4	5	6	7	8	9
Dataset	*ACS GA*[1]	*NHTS GA*[2]	*NHTS HH reps*[2]	*Follow-up survey opt-in observed*[2]	*Follow-up survey opt-in predicted*[2†]	*Follow-up survey final observed*[2]	*Follow-up survey final predicted*[2‡]	*Percent change*[3]	*Effect size*[3]
Age									
18-24	0.13	0.13	0.043	0.046	0.053	0.018	0.025	-0.81	0.43**
25-34	0.18	0.17	0.16	0.18	0.18	0.09	0.11	-0.37	
35-44	0.18	0.19	0.20	0.22	0.20	0.16	0.17	-0.04	
45-54	0.18	0.17	0.20	0.19	0.20	0.22	0.20	0.12	
55-64	0.16	0.17	0.20	0.21	0.19	0.26	0.23	0.42	
65+	0.17	0.17	0.20	0.17	0.17	0.25	0.26	0.52	
Gender									
Male	0.48	0.48	0.41	0.41	0.42	0.45	0.44	-0.08	0.08
Female	0.52	0.52	0.59	0.59	0.58	0.55	0.56	0.07	
Education									
Less than a high school graduate	0.062	0.070	0.051	0.042	0.052	0.019	0.038	-0.38	0.61***
High school graduate or GED	0.36	0.25	0.20	0.18	0.20	0.19	0.17	-0.53	
Some college or associates degree	0.30	0.30	0.31	0.32	0.31	0.27	0.29	-0.02	
Bachelor's degree	0.17	0.21	0.24	0.24	0.23	0.26	0.24	0.36	
Graduate degree or professional degree	0.10	0.17	0.21	0.21	0.21	0.26	0.26	1.53	
Worker	0.59	0.62	0.63	0.62	0.62	0.59	0.56	-0.05	0.06
Hispanic	0.078	0.083	0.075	0.066	0.073	0.058	0.058	-0.26	0.08
Asian/Pacific Islander	0.046	0.039	0.034	0.025	0.026	0.0090	0.017	-0.63	0.14*
Black	0.31	0.31	0.32	0.35	0.33	0.26	0.26	-0.18	0.12*
Native American	0.0090	0.0036	0.0037	0.0017	0.0033	0.0034	0.0028	-0.69	0.07
White	0.62	0.63	0.62	0.60	0.62	0.70	0.70	0.13	0.17*
Commute mode									
Private vehicle	0.94	0.93	0.92	0.90	0.91	0.96	0.93	-0.02	0.16*
Taxi	0.0030	0.0077	0.0050	0.0079	0.0091	0.0017	0.0059	0.97	
Public transit	0.022	0.032	0.041	0.055	0.042	0.017	0.032	0.44	
Walk	0.016	0.018	0.022	0.022	0.021	0.007	0.018	0.13	
Bike	0.0025	0.0065	0.0090	0.013	0.012	0.015	0.0085	2.40	

Other	0.013	0.0074	0.0050	0.005	0.007	0.00	0.0077	-0.41	
Commute time									
0-10 min	0.21	0.21	0.21	0.22	0.21	0.18	0.21	-0.01	0.17*
10-20 min	0.30	0.26	0.27	0.27	0.27	0.25	0.27	-0.11	
20-30 min	0.21	0.20	0.19	0.18	0.18	0.18	0.17	-0.16	
30-60 min	0.23	0.27	0.27	0.27	0.27	0.34	0.28	0.21	
60-90 min	0.033	0.048	0.047	0.052	0.044	0.036	0.050	0.53	
90+ min	0.015	0.026	0.017	0.019	0.020	0.015	0.020	0.28	

(b) Household-level

Column number	1	2	3	4	5	6	7	8	9
Dataset	*ACS GA*[4]	*NHTS GA*[5]	*NHTS HH reps*[5]	*Follow-up survey opt-in observed*[5]	*Follow-up survey opt-in predicted*[5†]	*Follow-up survey final observed*[5]	*Follow-up survey final predicted*[5‡]	*Percent change*[3]	*Effect size*[3]
Household size									
1	0.27	0.28	0.28	0.31	0.32	0.31	0.31	0.14	0.12*
2	0.33	0.33	0.33	0.29	0.31	0.33	0.35	0.05	
3+	0.40	0.39	0.39	0.40	0.37	0.36	0.34	-0.14	
Household income									
Less than $24,999	0.22	0.27	0.27	0.29	0.29	0.22	0.23	0.04	0.08
$25,000 to $49,999	0.23	0.23	0.23	0.23	0.23	0.25	0.22	-0.08	
$50,000 to $74,999	0.18	0.16	0.16	0.14	0.15	0.17	0.17	-0.06	
$75,000 to $99,999	0.12	0.11	0.11	0.11	0.10	0.09	0.12	-0.05	
$100,000 to $149,999	0.13	0.14	0.14	0.13	0.13	0.16	0.15	0.14	
More than $150,000	0.11	0.086	0.086	0.10	0.10	0.12	0.12	0.05	
Vehicle ownership									
0	0.067	0.078	0.078	0.091	0.092	0.040	0.062	-0.07	0.10*
1	0.33	0.35	0.35	0.37	0.37	0.36	0.34	0.03	
2	0.38	0.34	0.34	0.33	0.32	0.36	0.34	-0.10	
3+	0.22	0.23	0.23	0.20	0.22	0.24	0.26	0.14	
Homeowner	0.63	0.62	0.62	0.57	0.58	0.75	0.75	0.20	0.25*
Number of children									
0	0.70	0.68	0.68	0.67	0.69	0.75	0.73	0.04	0.10*
1	0.13	0.13	0.13	0.14	0.13	0.10	0.13	-0.02	
2	0.11	0.12	0.12	0.12	0.12	0.11	0.11	-0.03	
3+	0.060	0.063	0.063	0.06	0.05	0.037	0.038	-0.37	

Notes: For each variable, the sum of category shares might not equal 1 due to rounding errors.
[1] ACS individual weights are applied.
[2] NHTS individual weights are applied.
[3] Comparison between the population distribution and follow-up survey predicted distribution (columns 1 and 7).
[4] ACS household weights are applied.
[5] NHTS household weights are applied.
[*] Small effect size (w = 0.10). [**] Medium effect size (w = 0.30). [***] Large effect size (w = 0.50).
[†] Calculated with $\mathrm{P}\left(y_i^S = 1\right)$. [‡] Calculated with $\mathrm{P}\left(y_i^S = 1, y_i^O = 1\right)$.

Beyond the biases breakdown, the sum of all biases and errors shown in Figure 2, which indicates the distribution divergence between the population and the predicted follow-up survey respondents, is of the most concern[6]. A small distribution divergence indicates that the follow-up survey sample is expected to be representative of the population, which is a positive sign that recruiting respondents from a preceding survey is efficient and reasonable. Otherwise, a large divergence indicates that a biased follow-up survey sample is expected, which may call for some sampling remedies to improve its representativeness. Accordingly, in Table 7, we present the percentage change (column 8) and effect size (ES, column 9) between the population (column 1) and the predicted follow-up survey respondents (column 7). The definition of ES (w) is as follows (Cohen, 1977):

$$w = \sqrt{\sum_{i=1}^{m} \frac{\left(P_{prd(i)} - P_{pop(i)}\right)^2}{P_{pop(i)}}}, \tag{23}$$

where m is the number of variable categories; $P_{prd(i)}$ is the predicted proportion of category i in the follow-up survey (Table 7, column 7); $P_{pop(i)}$ is the actual proportion of category i in the population (Table 7, column 1). In general, a smaller ES indicates similar distributions. Cohen (1977) provides references for ES magnitudes: effect sizes of 0.10, 0.30, and 0.50 are considered as small, medium, and large, respectively.

Among the individual-level variables (Table 7a), the distribution of education and age in the follow-up survey samples diverge most widely from the corresponding

[6] The distribution divergence between the population and the *observed* follow-up survey respondents is of interest in an *ex post* analysis, but here we focus on *ex ante* applications of the PSS such as those in Scenarios 2 and 3 of Table 2. The distribution divergence metrics could serve as benchmarks in Section 6.2.

population distribution. Specifically, the follow-up survey respondents overrepresent highly educated and older groups. In the case of education, we see that the bias begins with the original set of NHTS respondents, and is amplified at the second stage of predicted response to the GDOT survey. The two commute-related variables show that we have a larger share of follow-up survey respondents who use non-private vehicles for commuting compared to the population, which might further contribute to the larger share of long commute times. The effect sizes of the household-level variables have overall smaller magnitudes than those of the individual-level variables (Table 7b). Homeownership has the largest effect size of 0.25. Specifically, the follow-up survey recruits a larger share of homeowners, which might relate to the survey mode (mailing) used for the follow-up survey: homeowners are more likely to receive the survey since they have permanent mailing addresses, while renters might not receive the follow-up survey due to address changes.

In Appendix B, we provide a visualization of selected variables shown in Table 7. The visualization presents the changing trajectories of the marginal distributions from the population to the predicted follow-up survey respondents.

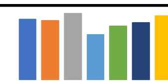
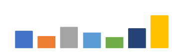
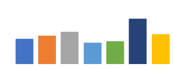
6.2 Outside Georgia: What does the follow-up survey sample look like?

In this section, we test the transferability of the PSS model to different populations, by checking the representativeness of follow-up survey respondents for selected states in diverse geographic regions of the US (west to east: California, Minnesota, North Carolina, New York and Massachusetts) and the full 2017 NHTS national sample. Table 8 presents the effect size by state.

In general, different regions have similar effect sizes for a given variable, which indicates a similar divergence level of the marginal distributions between the follow-up survey respondents and the populations in different regions. In that respect, the results show respectable generalizability of the PSS model across different areas. Nevertheless, the effect sizes do vary by state, which might point to regional differences that are not captured by the current PSS model. Moreover, the variations in effect size are not consistent across variables. For example, New York has the most representative follow-up survey sample regarding gender among the seven regions, but is the least representative on commute mode, household vehicles, and homeownership. Some of these large effect sizes of New York doubtless result from its diverse population composition and different lifestyles (e.g., large share of public transit use) compared to other states. Clearly, a model for Georgia is not seamlessly transferable to New York, but then it appears that a model for many other states would not be transferable to New York, either. Aside from New York, the model for Georgia seems to transfer relatively well to states that are dissimilar to it in many ways, including California and Massachusetts, as well as to the United States as a whole.

Overall, similar to findings in the previous section, the follow-up survey respondents are less representative in terms of age and education among the individual-level variables. Homeownership is the household-level variable that is hardest to represent in the follow-up survey. Appendix C provides marginal distributions of the variables in the selected geographic regions.

Table 8 – Effect size by different geographic regions

	GA	US	CA	MN	NC	NY	MA	ES by region[1]
Individual-level								
Age	0.43	0.45	**0.50**	0.41	0.44	0.49	0.48	
Gender	0.08	0.10	0.08	0.13	**0.14**	0.06	0.10	
Education	0.61	0.60	**0.67**	0.46	0.54	0.58	0.65	
Worker	0.06	0.07	0.09	0.08	**0.11**	0.05	0.08	
Hispanic	0.08	0.11	0.14	0.15	0.05	**0.16**	0.15	
Asian/Pacific Islander	0.14	0.15	**0.20**	0.10	0.09	0.19	0.12	
Black	0.12	0.09	0.07	0.10	0.09	**0.18**	0.10	
Native American	0.07	0.08	0.07	**0.13**	0.08	0.07	0.08	
White	0.17	0.18	0.32	0.13	0.12	**0.37**	0.18	
Commute mode	0.16	0.10	0.17	0.22	0.15	**0.33**	0.16	
Commute time	0.17	0.12	0.21	0.15	0.11	0.20	**0.33**	
Household-level								
Household size	0.12	0.13	0.16	**0.16**	0.13	0.03	0.16	
Household income	0.08	0.06	0.05	**0.20**	0.05	0.13	0.11	
Household vehicles	0.10	0.12	0.05	0.09	0.06	**0.43**	0.13	
Homeowner	0.25	0.29	0.33	0.21	0.23	**0.46**	0.30	
No. of children	0.10	0.08	0.09	0.12	0.09	0.09	**0.12**	

Note: Bolded numbers are the maximum effect size by row.
[1] Visualization of the effect size for each state in the same order as presented in the table.

CHAPTER 7. A COMPARISON OF REMEDIES FOR SAMPLING BIAS: SAMPLE SELECTION MODELS VERSUS WEIGHTING

In previous chapters, we identified multiple bias sources (e.g., self-selection, non-response) when recruiting respondents from a preceding travel survey. In this chapter, we analyze the consequence of the sample biases by assessing their influence on travel behavior models (in this case, vehicle-miles driven, VMD). Specifically, we explore two techniques for remedying sample biases, namely, sample selection models and sample weights. Figure 3 illustrates the two remedy paths and the internal-external evaluation procedure we implement, together with the conclusions we draw in this empirical application.

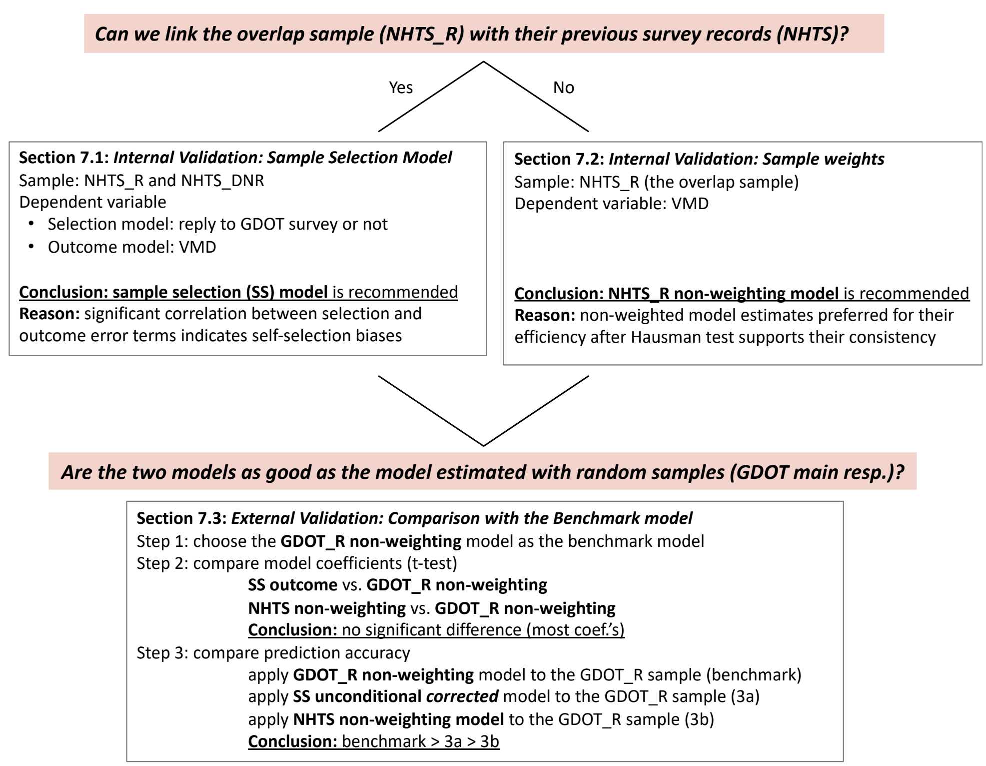


Figure 3 – Analysis flow chart

First, we evaluate the necessity of applying the two remedy techniques when modeling the travel behavior of a biased sample recruited from a preceding travel survey. The two techniques, sample selection models and sample weights, are applied under different conditions. Specifically, if we can link survey responses between the preceding and the follow-up surveys, we proceed to the sample selection model path (Section 7.1). Otherwise, we consider applying sample weights when modeling (Section 7.2).

Second, we conduct an external validation by comparing the two techniques with the benchmark model (i.e., a model calibrated on the address-based random sample). We compare model coefficients and prediction accuracies to further examine the quality of the proposed remedy techniques.

7.1 Internal Validation: Sample Selection Models

The sample selection (SS) model has a similar structure to the probit with sample selection (PSS) model presented and applied in Chapters 4-6. More specifically, the SS model is the prototype of the PSS model. Both SS and PSS models have a selection model and an outcome model. The selection model acts as a filter, which controls whether or not a case enters the outcome model. The difference between the SS and PSS models mainly resides in the outcome model. The SS model is designed for continuous dependent variables (e.g., VMD in our case) while the PSS model is designed for binary dependent variables (e.g., replying or not replying to the follow-up survey). Please refer to Appendix D for more details about the SS model.

In the SS model system, the selection model analyzes the response behavior to the follow-up survey, which requires knowing the characteristics of people who replied to the follow-up survey (NHTS_R) and who did not reply to the follow-up survey (NHTS_DNR). Those characteristics are collected from the preceding survey (i.e., NHTS in this application). The outcome model analyzes the travel behavior (i.e., VMD) of NHTS_R using data collected from the follow-up survey. Since the SS model estimates selection and outcome models simultaneously, we can apply the SS model to remedy the sample biases if and only if we can link survey records between the preceding and the follow-up surveys for the overlapped sample (i.e., NHTS_R). In this thesis, we are able to link survey records between the 2017 NHTS and the GDOT survey for NHTS_R and thus we can estimate a SS model using our dataset. Table 9 presents the model results.

As aforementioned, the selection model analyzes NHTS respondents' response behavior to the GDOT survey, which consists of two sequential decisions: (1) whether the respondent is willing to participate in follow-up surveys and (2) for the opt-in respondents, whether they actually reply to the GDOT survey. In Chapter 4, we analyzed the two decisions separately using a PSS model. Here, the selection model itself combines the two-step decision-making procedure[7] and thus we choose explanatory variables for the selection model based on the PSS model.

The selection model obtains results consistent with the PSS model. In general, old, white, highly educated homeowners from smaller households are more likely to reply to the GDOT survey. GDOT responders are likely to conduct more trips and are less sensitive about sharing personal information in the survey. They are also more likely to live in less

[7] Specifically, we combine both those not willing to participate in follow-up surveys (group W0 in Figure 1) and those who express willingness but do not respond to the follow-up survey (group W1R0) into a single group of non-responders (NHTS_DNR), while the group of responders to the follow-up survey (W1R1 in Figure 1) is here referred to as NHTS_R, the overlap sample.

dense areas. In the PSS model, an interesting finding was that homeowner, age, and medical condition had opposing signs in the two-step analysis, which indicates reverse effects of the three variables on response willingness (self-selection) and respondents' actual behavior (non-response). However, when we combine the response willingness and actual response behavior in the present selection model, we find that the three variables have the same signs as their counterparts in the PSS *outcome* model, indicating that the three variables have more dominant effects on influencing the survey response behavior than the response willingness.

The outcome model includes attitudes, sociodemographic, and land use characteristics as explanatory variables. Here we note that some variables are insignificant, but we still keep them to enable coefficient comparisons across different models. Among attitudes, the car owning attitude is significant, and the positive sign indicates that people who have a strong preference for owning a vehicle tend to have a higher weekly VMD. The sociodemographic variables are all significant. Specifically, characteristics such as being white, male, or a worker contribute to a higher weekly VMD. People from wealthier households with more vehicles also have higher weekly VMD.

Both error term parameters (σ and ρ) are highly significant, and the correlation (ρ) between the error terms of the selection and outcome models is sizeable (-0.454). The significant and sizeable correlation indicates that the self-selection and non-response biases, if not corrected, would influence the estimated effects of other variables on travel behavior collected in the follow-up survey (i.e., VMD in the GDOT survey) and shows the necessity of applying the SS model when analyzing travel behaviors observed in the follow-up survey. As such, based on our results, we recommend applying the sample selection model to remedy the sample biases resulting from the recruitment method if the dataset can meet the modeling standard (i.e., having survey record linkage between the preceding and the follow-up surveys).

Table 9 – Sample selection model results

Variable	$\hat{\boldsymbol{\gamma}}$	**S.E.**	**t-value**
Selection model: response to the GDOT survey			
Sociodemographic			
Household size (natural log-transformed)	-0.109**	0.036	-3.018
Homeowner	0.296***	0.047	6.237
Age	0.006***	0.001	4.308
Race: white	0.100*	0.042	2.398
Education	0.083***	0.016	5.334
Worker	-0.098*	0.040	-2.460
Has a medical condition	-0.178**	0.056	-3.193
Born in US	0.213**	0.072	2.974
Travel-related characteristics			
No. of trips on diary day	0.053***	0.006	9.101
Survey-related characteristics			
Household income - missing	-0.756***	0.130	-5.827
VMD - "I don't know"	-0.241***	0.042	-5.710
VMD - "I prefer not to answer"	-0.325*	0.163	-1.991
Land use characteristics			
Housing units per sq. mi.	-0.063***	0.018	-3.616
Constant	-1.754***	0.104	-16.919
Outcome model: $\boldsymbol{ln(VMD+1)}$	$\hat{\boldsymbol{\beta}}_N^{SS}$	**S.E.**	**t-value**
Attitudes			
Travel liking	0.030	0.023	1.266
Commute benefit	-0.026	0.024	-1.086
Family-oriented	0.038	0.024	1.599
Car owning	0.109***	0.024	4.509
Polychronic	0.035	0.024	1.463
Sociodemographic			
Race: white	0.161*	0.066	2.427
Female	-0.185***	0.048	-3.887
Worker	0.508***	0.051	10.047
Household income	0.084***	0.018	4.791
Household vehicles	0.085***	0.026	3.292
Land use characteristics			
Rural area	0.091	0.068	1.331
Constant	4.353***	0.217	20.050
Error terms			
σ	0.907***	0.046	19.699
ρ	-0.454***	0.116	-3.909

7.2 Internal Validation: Sample Weights

Linking survey records between preceding and follow-up surveys is required when applying the SS model to remedy the sample biases resulting from the proposed recruitment method. However, linkage between the two surveys might not always be available (e.g., a stricter privacy policy might prevent identifying respondents to the extent needed to link survey records). For survey developers who still want to use the proposed recruitment method, applying sample weights might help remedy the self-selection and non-response biases. In this section, we compare the unweighted ordinary least squares (OLS) model and the weighted ordinary least squares (WOLS) model to examine the necessity of applying sample weights to remedy the sample biases.

Indeed, applying sample weights is a common technique for addressing such biases regardless of whether they arose from prior survey completion or from a de novo sample recruitment. But recruiting survey respondents from a preceding travel survey might be particularly problematic, in that the sampling bias could be related to the travel behavior of interest and thus cause potential endogeneity in the modeling stage, which would mean that OLS would yield inconsistent coefficient estimators. As we have seen from the PSS model results (Section 5.1), multiple variables related to travel behaviors/ attitudes (e.g., number of trips on the diary day, transit usage frequency, awareness of one's VMD) influence self-selection into the follow-up survey, which might be confounded with the travel behaviors/attitudes collected in the follow-up survey (e.g., weekly VMD), and thus influence the OLS estimates. Indeed, we see that the average VMD of the NHTS_R respondents (134.22 mi) is significantly smaller than that of the GDOT_R respondents

(156.45 mi, $t\ stat = -4.428, d.f. = 3015.133, p = 0.000$). Accordingly, we consider applying sample weights in the modeling stage to remedy the potential endogeneity.

The ordinary least squares (OLS) method is one of the most commonly used estimation methods for linear regression models. Eq. 24 presents the formulation of the linear regression model, where y_i is the dependent variable for individual i; $\boldsymbol{x_i}$ is the vector of explanatory variables; $\boldsymbol{\beta}$ is the corresponding coefficient vector, and ε_i is the error term ($\boldsymbol{\varepsilon} \sim \boldsymbol{MVN}(\mathbf{0}, \sigma_\varepsilon^2 \boldsymbol{I})$). Under OLS estimation, the model coefficient estimators and the corresponding variance-covariance matrix of the estimators is provided by Eqs. 25-26. When we introduce sample weights into the estimation procedure, the coefficient estimators are provided by Eq. 27, where $\boldsymbol{W}$ is the diagonal matrix with sample weights on the main diagonal. However, applying sample weights introduces heteroscedasticity to the data, and therefore the estimator (co)variances should be calculated through Eq. 28, where $\boldsymbol{\Omega} = \sigma_\varepsilon^2 \boldsymbol{W}^{-1}$ (Winship and Radbill, 1994). Here we note that applying sample weights to an OLS model (i.e., the WOLS model) is different from the weighted least squares (WLS) model, where the latter model derives weights from the non-constant variance of the error terms to remedy the heteroscedasticity residing in the data, rather than applying external sample weights.

As mentioned above, if sampling biases are endogenous (directly or indirectly caused by the dependent variable of interest, at least in part), OLS estimators are inconsistent and WOLS estimators, which are consistent, should be preferred. If the sampling biases are exogenous, however, OLS estimators are consistent, and if consistent, they are more efficient than WOLS estimators and therefore OLS should be preferred. For a particular sample, the Hausman test assesses the consistency of OLS estimators by comparing the empirical estimates to their WOLS counterparts: if the two sets of estimates are sufficiently similar, within sampling variability (i.e., if the test statistic, which measures the discrepancy between the two sets of estimates, is small), the conclusion is that the OLS estimators are also consistent (Greene, 2012).

$$y_i = \boldsymbol{x_i}\boldsymbol{\beta} + \varepsilon_i, \tag{24}$$

$$\widehat{\boldsymbol{\beta}}^{OLS} = (\boldsymbol{X}'\boldsymbol{X})^{-1}\boldsymbol{X}'\boldsymbol{y} \tag{25}$$

$$Cov(\widehat{\boldsymbol{\beta}}^{OLS}) = \sigma_\varepsilon^2(\boldsymbol{X}'\boldsymbol{X})^{-1} \tag{26}$$

$$\widehat{\boldsymbol{\beta}}^{WOLS} = (\boldsymbol{X}'\boldsymbol{W}\boldsymbol{X})^{-1}\boldsymbol{X}'\boldsymbol{W}\boldsymbol{y} \tag{27}$$

$$Cov(\widehat{\boldsymbol{\beta}}^{OLS}) = (\boldsymbol{X}'\boldsymbol{X})^{-1}\boldsymbol{X}'\boldsymbol{\Omega}\mathbf{X}(\boldsymbol{X}'\boldsymbol{X})^{-1} \tag{28}$$

Table 10 presents the model results for both weighted and unweighted models. Similar to the SS outcome model results, people who prefer owning vehicles tend to have a higher weekly VMD. Characteristics such as being white, male, a worker, and from wealthier households with more vehicles contribute to a higher weekly VMD.

To assess the influence of endogeneity, we conduct Hausman's test to compare OLS estimates with WOLS estimates. The test result ($\chi^2 = 2.916, d.f. = 12,\ p = 0.996$) fails to reject the null hypothesis that the OLS estimators are consistent. There are two possible implications. First, the result might indicate that the endogeneity residing in the self-selection process is not severe enough to cause substantial biases in the OLS estimates, which would explain why the OLS estimates are not significantly different from the WOLS ones. Alternatively, however, it may be that the sample weights used in the WOLS model do not effectively correct the biases caused by endogeneity (i.e., the WOLS estimates are as biased as the OLS estimates). One direction for future research is to include travel behaviors (e.g., VMD) as control variables when generating sample weights for the WOLS model. Taking the results of the current Hausman's test at face value, however, in this instance we prefer OLS over WOLS since OLS estimates appear to be consistent and are, in that case, more efficient.

Table 10 – OLS and WOLS model results (sample: NHTS_R, N=1,357)

	OLS model			WOLS model		
Variable	$\boldsymbol{\beta_N^{OLS}}$	**S.E.**	**t-value**	$\boldsymbol{\beta_N^{WOLS}}$	**S.E.**	**t-value**
Attitudes						
Travel liking	0.033	0.024	1.382	0.078	0.071	1.091
Commute benefit	-0.029	0.024	-1.208	-0.043	0.064	-0.666
Family-oriented	0.040$^{\cdot}$	0.024	1.655	-0.014	0.071	-0.193
Car owning	0.112***	0.024	4.624	0.137*	0.068	2.013
Polychronic	0.032	0.024	1.329	0.058	0.071	0.818
Sociodemographic						
Race: white	0.228***	0.062	3.661	0.281$^{\cdot}$	0.159	1.764
Female	-0.196***	0.048	-4.103	-0.221	0.140	-1.576
Worker	0.458***	0.048	9.503	0.477***	0.144	3.307
Household income	0.101***	0.017	5.963	0.065	0.047	1.378
Household vehicle	0.073**	0.026	2.863	0.101	0.073	1.390
Land use characteristics						
Rural area	0.094	0.069	1.357	0.130	0.151	0.865
Constant	3.708***	0.089	41.571	3.712***	0.222	16.746

7.3 External Validation: Comparison with the Benchmark Model

In the previous sections, we examined the necessity of applying sample selection (SS) models and sample weights under different circumstances. Overall, the SS model is recommended if we can link survey records between the preceding and the follow-up surveys. Otherwise, we recommend the OLS model over the WOLS model since the former one provides more efficient estimates. In this section, we conduct an external validation of the two recommended models (SS and OLS models) by comparing them to the benchmark model estimated on the address-based random sample.

Table 11 summarizes the three sets of model estimates and the comparison results. The benchmark model consists of the OLS estimates based on the address-based random sample (GDOT_R). The SS outcome model is estimated using respondents recruited from the 2017 NHTS (NHTS_R) after the sample selection correction (i.e., the outcome model in Table 9). The OLS model consists of the OLS estimates using GDOT survey respondents recruited from the 2017 NHTS (i.e., the OLS model in Table 10).

We first conduct t-tests for differences between the coefficients of the benchmark model and the two proposed models, respectively. Please note, the sample used for the benchmark model (GDOT_R) is independent from that used for the SS and OLS models (NHTS_R). The results do not show significant differences for most coefficients. The coefficient of the car-owning attitude in the SS outcome model is smaller than the corresponding coefficient in the benchmark model at the 0.05 significance level. The same coefficient in the OLS model is smaller than its benchmark model counterpart at the 0.1 significance level. The coefficient of race in the OLS model is marginally greater than the benchmark coefficient. The indicator of living in a rural area is significant in the benchmark model, indicating that living in rural areas is related to a higher VMD. However, the variable is insignificant in both remedy models, which contributes to the marginally significant results of the coefficient t-tests with the benchmark model. Overall, the SS model coefficients range from 45% to 194% of their benchmark counterparts' values if the universally insignificant coefficients are excluded. The OLS model coefficients range from 50% to 156% of their benchmark counterparts' values if the universally insignificant coefficient "rural" is excluded. The two proposed models have fewer significant coefficients for the attitudinal variables.

Table 11 – Benchmark model and coefficient comparisons

Sample	Benchmark OLS model GDOT_R (N=1,680)		SS outcome model NHTS_R (N=1,357)				OLS model NHTS_R (N=1,357)			
Variable	$\hat{\beta}_G^{OLS}$	**S.E.**	$\hat{\beta}_N^{SS}$	**S.E.**	$\hat{\beta}_N^{SS}$ vs. β_G^{OLS} *t-value*	*ratio*	$\hat{\beta}_N^{OLS}$	**S.E.**	$\hat{\beta}_N^{OLS}$ vs. $\hat{\beta}_G^{OLS}$ *t-value*	*ratio*
Attitudes										
Travel liking	**0.051**	0.023	0.030	0.023	*-0.65*	0.58	0.033	0.024	*-0.55*	0.64
Commute benefit	**-0.058**	0.022	-0.026	0.024	*1.00*	0.45	-0.029	0.024	*0.89*	0.50
Family-oriented	**0.077**	0.023	0.038	0.024	*-1.19*	0.50	0.040	0.024	*-1.13*	0.52
Car owning	**0.178**	0.023	**0.109**	0.024	*-2.07*	0.61	**0.112**	0.024	*-1.95*	0.63
Polychronic	**0.049**	0.023	0.035	0.024	*-0.42*	0.71	0.032	0.024	*-0.51*	0.65
Sociodemographic										
Race: white	0.083	0.056	**0.161**	0.066	*0.90*	1.94	**0.228**	0.062	*1.73*	2.75
Female	**-0.285**	0.048	**-0.185**	0.048	*1.48*	0.65	**-0.196**	0.048	*1.31*	0.69
Worker	**0.484**	0.048	**0.508**	0.051	*0.34*	1.05	**0.458**	0.048	*-0.39*	0.95
Household income	**0.088**	0.016	**0.084**	0.018	*-0.15*	0.96	**0.101**	0.017	*0.57*	1.15
Household vehicle	**0.047**	0.024	**0.085**	0.026	*1.07*	1.80	**0.073**	0.026	*0.75*	1.56
Land use characteristics										
Rural area	0.584	0.275	0.091	0.068	*-1.74*	0.16	0.094	0.069	*-1.73*	0.16
Constant	**3.935**	0.091	**4.353**	0.217	*1.77*	1.11	**3.708**	0.089	*-1.78*	0.94

Note: Bolded coefficients are significant at the 0.05 level or better. Underlined t-values mean the coefficient comparison statistic is significant at the 0.1 level or better.

Next, we calculate the prediction accuracy of the two proposed models as well as that of the benchmark model. We expect the benchmark model to best represent the travel behavior (VMD) of a random sample of Georgia adults since it was estimated on such a random sample (or as close to it as we could get) while the other two models were not. Furthermore, prediction accuracy for the benchmark model is based on applying it to the same data on which it was estimated, whereas for the other two models it is based on applying them to a different sample (i.e., the benchmark model sample). It is thus expected that the benchmark model will have the highest prediction accuracy. However, it is relevant to ask whether the other two models have similar prediction accuracies to each other, and whether they have a materially worse performance than that of the benchmark model. Specifically, we apply the three models to the address-based random sample (GDOT_R) and calculate four prediction accuracy measures, namely R^2, adjusted R^2, $RMSE$ and adjusted $RMSE$. For each measure, we generate both weighted and non-weighted versions (see Table 12 for equations). Overall, a higher R^2 and a lower $RMSE$ indicate higher prediction accuracies.

Table 12 – Model metrics

Unweighted	Eq.	Weighted	Eq.
$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$	(29)	$R^2_{wt} = 1 - \frac{\sum w_i * (y_i - \hat{y}_i)^2}{\sum w_i * (y_i - \bar{y}_{wt})^2}$	(30)
$R^2_{adj} = 1 - \frac{\sum(y_i - \hat{y}_i)^2/(n-p-1)}{\sum(y_i - \bar{y})^2/(n-1)}$	(31)	$R^2_{wt\,adj} = 1 - \frac{\sum w_i * (y_i - \hat{y}_i)^2/(n-p-1)}{\sum w_i * (y_i - \bar{y}_{wt})^2/(n-1)}$	(32)
$RMSE = \sqrt{\sum \frac{(y_i - \hat{y}_i)^2}{n}}$	(33)	$RMSE_{wt} = \sqrt{\sum \frac{w_i * (y_i - \hat{y})^2}{n}}$	(34)
$RMSE_{adj} = \sqrt{\sum \frac{(y_i - \hat{y}_i)^2}{n-p}}$	(35)	$RMSE_{wt\,adj} = \sqrt{\sum \frac{w_i * (y_i - \hat{y}_i)^2}{n-p}}$	(36)

Note: y_i is the observed value of VMD for the i^{th} case, $\hat{y}_i$ is the predicted value, $\bar{y}$ is the non-weighted mean of y_i, $\bar{y}_{wt}$ is the weighted mean of y_i, w_i is the sample weight, n is the sample size, and p is the number of coefficients.

Table 13 presents the prediction accuracy results. The sample selection model and the OLS model have similar performances, with the SS model having a slightly higher prediction accuracy. Here, we note that the SS outcome model could not be directly applied to the prediction exercise. Eq. 37 presents the prediction formula. Specifically, the $\rho\sigma\lambda(\boldsymbol{z_i\gamma})$ term corrects for the self-selection and non-response biases captured in the selection model. However, since the GDOT_R respondents lack variables used in the correction term, we calculate the average effect of the selection model (i.e., the average inverse Mills' ratio of the calibration dataset, -0.589) and use it as a heuristic correction in the prediction exercise.

$$\begin{aligned} E\left[y_i^O \middle| y_i^{S^*} > 0\right] &= E\left[y_i^O \middle| \varepsilon_i^S > -\boldsymbol{z_i\gamma}\right] = \boldsymbol{x_i\beta_N^{SS}} + E\left[\varepsilon_i^O \middle| \varepsilon_i^S > -\boldsymbol{z_i\gamma}\right] \\ &= \boldsymbol{x_i\beta_N^{SS}} + \rho\sigma\lambda(\boldsymbol{z_i\gamma}) \end{aligned} \tag{37}$$

Table 13 – Prediction accuracy

Application dataset: GDOT subsample	R^2	R^2_{adj}	$RMSE$	$RMSE_{adj}$
Benchmark OLS model (estimated on GDOT_R)				
Non-weighted	0.194	0.189	0.900	0.903
Weighted	0.234	0.229	0.947	0.950
OLS model (estimated on NHTS_R)				
Non-weighted	0.182	0.176	0.907	0.910
Weighted	0.209	0.203	0.962	0.966
SS outcome model (corrected)				
Non-weighted	0.183	0.169	0.907	0.914
Weighted	0.210	0.197	0.961	0.970
SS outcome model				
Non-weighted	-0.174	-0.194	1.087	1.096
Weighted	-0.097	-0.116	1.133	1.142

CHAPTER 8. CONCLUSION

In this thesis, we identified and analyzed the self-selection bias existing in follow-up survey respondents who were recruited from a preceding travel survey (the 2017 NHTS). We applied a probit with sample selection (PSS) model to examine the willingness of NHTS respondents to participate in a follow-up survey, together with their actual response behavior. To our knowledge, this is the first study that uses the PSS model to analyze sample biases residing in consecutive survey recruitment. Overall, as expected, we identified self-selection biases among survey respondents recruited from a preceding household travel survey. Findings suggest that the requirements of the preceding survey influenced respondents' willingness to participate in follow-up surveys. In the particular context of NHTS, respondents from survey-burdensome households (e.g., large households) were less likely to report being willing to respond to a follow-up survey. Respondents' attitudes towards privacy and travel-liking were also influential to their willingness to be contacted for a follow-up survey. Respondents from specific groups (e.g., travel-restricted people, frequent transit users) were more likely to report being willing to participate in a follow-up survey. By participating in travel surveys, these groups may be seeking to improve the quality of their travel. We also found three explanatory variables with opposing signs between the selection and outcome models, a finding that indicated inconsistencies between people's reported willingness (to participate in a survey) and their actual (response) behaviors. Similarly, the negative error term correlations signified that, on net, unobserved characteristics had impacts on selection that were opposite to their impacts on the outcome.

PSS models do not have model performance measures that are consistently reported in the literature. To address this gap, this thesis summarizes six well-known model performance measure categories, adjusted based on the PSS model structure: the log-likelihood, McFadden's pseudo-R^2, information criteria, point-biserial correlation coefficient, root mean squared error, and success table. McFadden's pseudo-R^2 bounds the model fit between 0 and 1, which is straightforward for understanding and could be used to compare across different PSS models. The success table provides overall model performance measures as well as performance measures for each alternative, which supplies information important to evaluating the model.

We analyzed the representativeness of the follow-up survey respondents regarding 17 selected variables, including sociodemographic and travel-related variables. We decomposed the divergence of the marginal distributions between the population and the predicted follow-up survey respondents into five components, namely dataset bias, household representative bias, self-selection bias, non-response bias, and prediction error. Results showed that the selection of the household representative contributed to a large proportion of the distribution divergence of individual-level variables. The effect sizes of differences between marginal distributions showed that education and age are the two least representative individual-level variables in the follow-up survey, whereas homeownership had the largest effect size among the household-level variables.

We also applied the PSS model to different geographic regions of the U.S., namely California, Minnesota, North Carolina, New York and Massachusetts (west to east). Similar effect sizes across states indicated good generalizability of the PSS model. Education, age, and homeownership were still poorly represented among predicted respondents to the follow-up survey for these other states. New York had less representative predicted follow-up survey respondents compared to other states, presumably a consequence of its diverse population composition and different transportation-related lifestyles.

Lastly, we analyze the *consequence* of self-selection biases by assessing their influence on travel behavior models developed on the second-stage sample. We examine and compare two techniques (i.e., sample selection models and sample weights) that could remedy the influence of unrepresentative samples recruited from a preceding survey on travel behavior models. Based on the results, we recommend applying the SS model to adjust the sample biases when the survey developer can link survey records between the preceding and the follow-up surveys. When the survey records cannot be linked between the two surveys, one should apply sample weights only if the appropriate Hausman test indicates it to be necessary for achieving estimator consistency, since sample weights introduce heteroscedasticity to the data and thus will decrease model estimation efficiency. A future research direction regarding sample weights is to include travel behavior variables in the weighting procedure (in the expectation that doing so could more effectively correct for any endogeneity in the sampling bias) and check how much they influence the model estimates.

Overall, this thesis can help survey developers assess the representativeness and cost-effectiveness of the proposed sampling frame (i.e., a pool of previous survey respondents), which in turn will suggest adjustments to the sampling frame that can improve the representativeness of the new sample. We recommend that large-scale travel surveys like the NHTS retain the willingness question as a recurring item, thereby allowing local agencies and researchers to efficiently recruit follow-up respondents from their sample. In fact, we recommend that the question be asked of *all* survey respondents, not only the main household respondent as was the case here. Recruiting future survey respondents from among *all* willing preceding survey respondents could substantially reduce sampling biases at the outset. When modeling travel behaviors using the sample recruited from the proposed sampling frame, we recommend applying sample selection models to adjust the inherent self-selection biases whenever possible.

APPENDIX A. MARGINAL DISTRIBUTIONS OF SELECTED VARIABLES (RANDOM SELECTION)

As discussed in Section 6.1, the household representative filter generates biases for individual-level variables. We would expect a more representative follow-up survey sample if the NHTS were to ask for every household member's willingness to participate in a follow-up survey. We simulate such a scenario by randomly selecting one adult from each household as the household representative and predicting their response to the follow-up survey. Table A1 presents the marginal distributions for randomly selected NHTS respondents (column 3a), the corresponding follow-up survey prediction (column 7a), and the effect size between the prediction and the population distribution (column 9a). Compared to the household representative prediction (column 9), the new effect sizes calculated from the randomly selected NHTS respondents are generally reduced, especially for the largest effect sizes (e.g., age, education).

Table A1 – Marginal distributions of selected individual-level variables (HH representatives versus random selection)

Column number	1	2	3	3a	7	7a	9	9a
Dataset	*ACS GA*[1]	*NHTS GA*[2]	*NHTS HH reps*[2]	*NHTS random*[2]	*Follow-up survey final predicted (HH reps)*[2‡]	*Follow-up survey final predicted (random)*[2‡]	*Effect size (HH reps)*[3]	*Effect size (random)*[4]
Age								
18-24	0.13	0.13	0.043	0.097	0.025	0.087	0.43**	0.26*
25-34	0.18	0.17	0.16	0.18	0.11	0.13		
35-44	0.18	0.19	0.20	0.20	0.17	0.17		
45-54	0.18	0.17	0.20	0.16	0.20	0.16		
55-64	0.16	0.17	0.20	0.18	0.23	0.19		
65+	0.17	0.17	0.20	0.19	0.26	0.25		
Gender								
Male	0.48	0.48	0.41	0.45	0.44	0.45	0.08	0.06
Female	0.52	0.52	0.59	0.55	0.56	0.55		
Education								
Less than a high school graduate	0.062	0.070	0.051	0.072	0.038	0.058	0.61***	0.44**
High school graduate or GED	0.36	0.25	0.20	0.23	0.17	0.22		
Some college or associates degree	0.30	0.30	0.31	0.30	0.29	0.29		
Bachelor's degree	0.17	0.21	0.24	0.22	0.24	0.23		
Graduate degree or professional degree	0.10	0.17	0.21	0.18	0.26	0.21		
Worker	0.59	0.62	0.63	0.62	0.56	0.55	0.06	0.08
Hispanic	0.078	0.083	0.075	0.078	0.058	0.062	0.08	0.06
Asian/Pacific Islander	0.046	0.039	0.034	0.034	0.017	0.028	0.14*	0.09
Black	0.31	0.31	0.32	0.33	0.26	0.23	0.12*	0.17*
Native American	0.0090	0.0036	0.0037	0.0029	0.0028	0.0031	0.07	0.06
White	0.62	0.63	0.62	0.61	0.70	0.72	0.17*	0.19*
Commute mode								
Private vehicle	0.94	0.93	0.92	0.92	0.93	0.93	0.16*	0.17*
Taxi	0.0030	0.0077	0.0050	0.011	0.0059	0.0068		
Public transit	0.022	0.032	0.041	0.035	0.032	0.028		
Walk	0.016	0.018	0.022	0.019	0.018	0.016		
Bike	0.0025	0.0065	0.0090	0.0083	0.0085	0.0058		
Other	0.013	0.0074	0.0050	0.0073	0.0077	0.010		

Commute time								
0-10 min	0.21	0.21	0.21	0.21	0.21	0.21	0.17*	0.17*
10-20 min	0.30	0.26	0.27	0.26	0.27	0.25		
20-30 min	0.21	0.20	0.19	0.19	0.17	0.20		
30-60 min	0.23	0.27	0.27	0.27	0.28	0.27		
60-90 min	0.033	0.048	0.047	0.042	0.050	0.041		
90+ min	0.015	0.026	0.017	0.024	0.020	0.027		

Notes: For each variable, the sum of category shares might not equal 1 due to rounding errors. Column numbers in Table A1 match the counterparts in Table 7.

[1] ACS individual weights are applied.

[2] NHTS individual weights are applied.

[3] Comparison between the population distribution and follow-up survey predicted distribution (HH representatives, columns 1 and 7a).

[4] Comparison between the population distribution and follow-up survey predicted distribution (random, columns 1 and 7b)

* Small effect size (w = 0.10). ** Medium effect size (w = 0.30). *** Large effect size (w = 0.50).

‡ Calculated with $P(y_i^S = 1, y_i^O = 1)$.

APPENDIX B. CHANGING TRAJECTORIES OF MARGINAL DISTRIBUTIONS

To further illustrate the changing trajectories of the marginal distributions from the population to the predicted follow-up survey respondents, we select two individual-level variables (i.e., age, gender) and two household-level variables (i.e., household size, household income) and visualize them in Figure B1 (for each figure, read lines from left to right).

Regarding the two individual-level variables, we see large differences between the NHTS Georgia population and NHTS household representatives. Specifically, household representatives underrepresent younger groups (i.e., 18-24 and 25-34) and males, meaning that middle-aged/older people (45+) and females are more likely to answer the household-related questions in the retrieval survey. In the observed opt-in follow-up survey sample, we see slightly increased shares of young and middle-aged people, which indicates that the self-selection bias partially offsets the HH representative bias. However, the non-response bias results in an even worse underrepresentation of younger people and overrepresentation of older people in the observed final follow-up survey. The marginal distribution of gender is relatively stable after the household representative filter (except for the small increase of males in the sample), which indicates small self-selection biases, non-response biases, and prediction errors.

The two household-level sociodemographic variables, namely, household size and household income, have fluctuating trajectories. Regarding household size, we see similar marginal distributions of the population (ACS) and the NHTS Georgia sample/household rep sample. The main distribution divergence occurs between the NHTS Georgia/household rep sample and the observed opt-in follow-up survey respondents. As we have discussed in the model result section, larger households are less willing to participate in a follow-up survey due to the heavy burden of survey completion that accompanies more family members. After the opt-in process, the proportion of households with three or more members keeps shrinking, while two-member households take the largest share in the final follow-up survey sample due to non-response biases and prediction errors.

Regarding household income, we see that the NHTS Georgia/household rep sample overrepresents the lower income group (less than $24,999) and underrepresents some middle/high-income groups ($50,000 to $99,999, $150,000 or more). The household income distribution of the observed opt-in follow-up sample diverges from the household income distribution of the NHTS Georgia/household rep sample, which indicates the self-selection biases. Interestingly, the traits of the observed final follow-up survey respondents partially *correct* some of the divergences, i.e., the marginal distribution of the *final* follow-up survey respondents is close to the population marginal distribution. In other words, the non-response biases partially offset the self-selection bias.

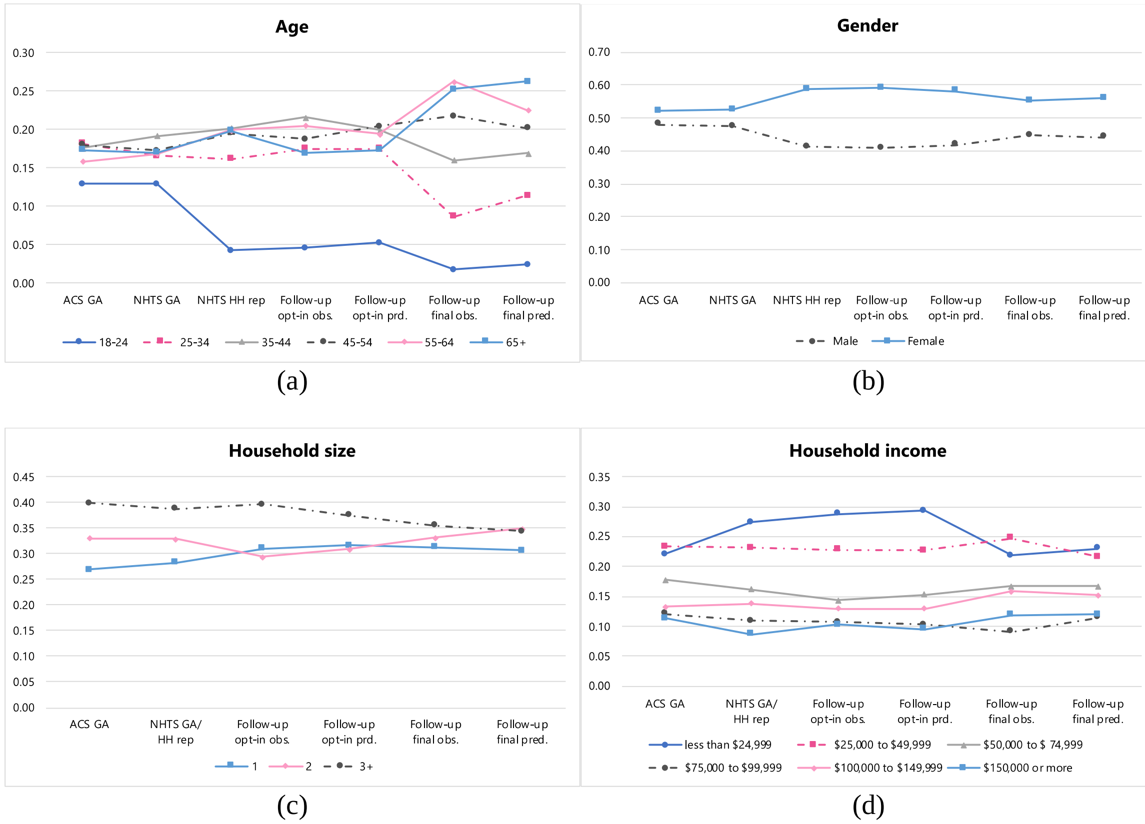


Figure B1. Changing trajectories of the marginal distributions

APPENDIX C. MARGINAL DISTRIBUTIONS FOR SELECTED GEOGRAPHIC REGIONS

Table C1. Marginal distributions of selected variables in the U.S. as a whole

(a) Individual-level

Column No.	1	2	3	7	8	9
Dataset	*ACS US*[1]	*NHTS US*[2]	*NHTS HH reps*[2]	*Follow-up survey final predicted*[2]	*Percent change*[3]	*Effect size*[3]
Age						
18-24	0.12	0.12	0.046	0.025	-0.80	0.45**
25-34	0.18	0.17	0.16	0.11	-0.41	
35-44	0.16	0.17	0.18	0.15	-0.09	
45-54	0.17	0.16	0.18	0.17	0.01	
55-64	0.17	0.18	0.21	0.24	0.44	
65+	0.20	0.20	0.23	0.31	0.56	
Gender						
Male	0.49	0.48	0.44	0.44	-0.10	0.10*
Female	0.51	0.52	0.56	0.56	0.09	
Education						
Less than a high school graduate	0.063	0.063	0.045	0.030	-0.52	0.60***
High school graduate or GED	0.34	0.23	0.18	0.16	-0.53	
Some college or associates degree	0.31	0.31	0.31	0.30	-0.03	
Bachelor's degree	0.18	0.22	0.25	0.25	0.39	
Graduate degree or professional degree	0.11	0.18	0.22	0.26	1.43	
Worker	0.60	0.63	0.63	0.56	-0.06	0.07
Hispanic	0.16	0.16	0.15	0.12	-0.27	0.11*
Asian/Pacific Islander	0.066	0.056	0.048	0.029	-0.56	0.15*
Black	0.13	0.12	0.14	0.10	-0.24	0.09
Native American	0.016	0.0082	0.0075	0.0056	-0.65	0.08
White	0.76	0.78	0.77	0.84	0.10	0.18*
Commute mode						
Private vehicle	0.90	0.88	0.87	0.91	0.01	0.10*
Taxi	0.0017	0.0032	0.0031	0.0013	-0.24	
Public transit	0.053	0.070	0.080	0.055	0.04	
Walk	0.028	0.026	0.030	0.021	-0.27	
Bike	0.0060	0.012	0.013	0.010	0.73	
Other	0.012	0.0069	0.0049	0.0049	-0.58	
Commute time						
0-10 min	0.24	0.25	0.25	0.26	0.07	0.12*
10-20 min	0.31	0.28	0.29	0.29	-0.06	
20-30 min	0.21	0.19	0.18	0.18	-0.15	
30-60 min	0.20	0.23	0.23	0.23	0.12	

60-90 min	0.027	0.039	0.037	0.037	0.39	
90+ min	0.016	0.018	0.015	0.014	-0.12	

(b) Household-level

Column No.	1	2	3	7	8	9
Dataset	*ACS US*[4]	*NHTS US*[5]	*NHTS HH reps*[5]	*Follow-up survey final predicted*[5]	*Percent change*[3]	*Effect size*[3]
Household size						
1	0.28	0.30	0.30	0.31	0.13	0.13*
2	0.34	0.33	0.33	0.37	0.07	
3+	0.38	0.37	0.37	0.32	-0.16	
Household income						
Less than $24,999	0.20	0.24	0.24	0.20	-0.03	0.06
$25,000to $49,999	0.22	0.22	0.22	0.22	0.01	
$50,000 to $74,999	0.18	0.16	0.16	0.17	-0.02	
$75,000 to $99,999	0.12	0.12	0.12	0.13	0.05	
$100,000 to $149,999	0.15	0.15	0.15	0.16	0.11	
More than $150,000	0.13	0.11	0.11	0.12	-0.10	
Vehicle ownership						
0	0.087	0.10	0.10	0.065	-0.25	0.12*
1	0.33	0.35	0.35	0.34	0.03	
2	0.37	0.33	0.33	0.35	-0.07	
3+	0.21	0.22	0.22	0.25	0.18	
Homeowner	0.63	0.64	0.64	0.77	0.22	0.29*
No. of children						
0	0.72	0.70	0.70	0.75	0.04	0.08
1	0.12	0.12	0.12	0.10	-0.12	
2	0.10	0.12	0.12	0.10	-0.01	
3+	0.057	0.056	0.056	0.043	-0.24	

Notes:
For each variable, the sum of the category shares might not equal 1 due to rounding errors.
[1] ACS individual weights are applied.
[2] NHTS individual weights are applied.
[3] Comparison between the population distribution and follow-up survey distribution (columns 1 and 5).
[4] ACS household weights are applied.
[5] NHTS household weights are applied.
* Small effect size (w = 0.10).
** Medium effect size (w = 0.30).
*** Large effect size (w = 0.50).

Table C2. Marginal distributions of selected variables in California

(a) Individual-level

Column No.	1	2	3	7	8	9
Dataset	*ACS CA*[1]	*NHTS CA*[2]	*NHTS HH reps*[2]	*Follow-up survey final predicted*[2]	*Percent change*[3]	*Effect size*[3]
Age						
18-24	0.13	0.13	0.042	0.022	-0.83	0.50***
25-34	0.20	0.17	0.16	0.10	-0.49	
35-44	0.17	0.19	0.21	0.17	-0.03	
45-54	0.17	0.17	0.19	0.19	0.08	
55-64	0.15	0.16	0.19	0.23	0.46	
65+	0.18	0.18	0.21	0.30	0.69	
Gender						
Male	0.49	0.49	0.46	0.45	-0.08	0.08
Female	0.51	0.51	0.54	0.55	0.08	
Education						
Less than a high school graduate	0.10	0.078	0.053	0.032	-0.68	0.67***
High school graduate or GED	0.28	0.19	0.13	0.11	-0.62	
Some college or associates degree	0.32	0.32	0.33	0.32	0.01	
Bachelor's degree	0.19	0.22	0.25	0.26	0.36	
Graduate degree or professional degree	0.11	0.18	0.24	0.28	1.57	
Worker	0.59	0.61	0.63	0.55	-0.07	0.09
Hispanic	0.35	0.36	0.34	0.28	-0.19	0.14*
Asian/Pacific Islander	0.17	0.15	0.13	0.10	-0.44	0.20*
Black	0.067	0.058	0.062	0.051	-0.24	0.07*
Native American	0.018	0.011	0.011	0.0089	-0.51	0.07
White	0.64	0.73	0.74	0.80	0.24	0.32**
Commute mode						
Private vehicle	0.89	0.87	0.85	0.88	-0.01	0.17*
Taxi	0.0016	0.0034	0.0033	0.0018	0.13	
Public transit	0.053	0.073	0.085	0.072	0.35	
Walk	0.028	0.028	0.032	0.023	-0.17	
Bike	0.011	0.016	0.022	0.020	0.92	
Other	0.016	0.0067	0.0025	0.0023	-0.85	
Commute time						
0-10 min	0.21	0.22	0.21	0.21	0.04	0.21*
10-20 min	0.30	0.26	0.26	0.25	-0.15	
20-30 min	0.21	0.19	0.17	0.17	-0.21	
30-60 min	0.22	0.27	0.29	0.28	0.27	
60-90 min	0.039	0.053	0.054	0.061	0.56	
90+ min	0.020	0.022	0.019	0.019	-0.01	

(b) Household-level

Column No.	1	2	3	7	8	9
Dataset	*ACS CA*[4]	*NHTS CA*[5]	*NHTS HH reps*[5]	*Follow-up survey final predicted*[5]	*Percent change*[3]	*Effect size*[3]
Household size						
1	0.24	0.26	0.26	0.29	0.21	0.16*
2	0.30	0.30	0.30	0.33	0.08	
3+	0.46	0.44	0.44	0.38	-0.16	
Household income						
Less than $24,999	0.18	0.21	0.21	0.17	-0.03	0.05
$25,000to $49,999	0.19	0.20	0.20	0.19	-0.02	
$50,000 to $74,999	0.16	0.15	0.15	0.15	-0.04	
$75,000 to $99,999	0.12	0.12	0.12	0.13	0.08	
$100,000 to $149,999	0.16	0.16	0.16	0.17	0.08	
More than $150,000	0.19	0.16	0.16	0.19	-0.03	
Vehicle ownership						
0	0.073	0.085	0.085	0.067	-0.08	0.05
1	0.31	0.33	0.33	0.32	0.05	
2	0.37	0.34	0.34	0.35	-0.06	
3+	0.25	0.24	0.24	0.26	0.05	
Homeowner	0.54	0.54	0.54	0.70	0.30	0.33**
No. of children						
0	0.70	0.67	0.67	0.72	0.03	0.09
1	0.13	0.13	0.13	0.11	-0.12	
2	0.12	0.15	0.15	0.12	0.07	
3+	0.062	0.062	0.062	0.046	-0.25	

Notes:
For each variable, the sum of the category shares might not equal 1 due to rounding errors.
[1] ACS individual weights are applied.
[2] NHTS individual weights are applied.
[3] Comparison between the population distribution and follow-up survey distribution (columns 1 and 5).
[4] ACS household weights are applied.
[5] NHTS household weights are applied.
* Small effect size (w = 0.10).
** Medium effect size (w = 0.30).
*** Large effect size (w = 0.50).

Table C3. Marginal distributions of selected variables in Minnesota

(a) Individual-level

Column No.	1	2	3	7	8	9
Dataset	*ACS MN*[1]	*NHTS MN*[2]	*NHTS HH reps*[2]	*Follow-up survey final predicted*[2]	*Percent change*[3]	*Effect size*[3]
Age						
18-24	0.12	0.13	0.037	0.026	-0.78	0.41**
25-34	0.18	0.18	0.18	0.12	-0.32	
35-44	0.16	0.16	0.18	0.15	-0.05	
45-54	0.17	0.15	0.15	0.16	-0.05	
55-64	0.17	0.18	0.22	0.25	0.41	
65+	0.20	0.20	0.23	0.29	0.48	
Gender						
Male	0.49	0.50	0.46	0.43	-0.13	0.13*
Female	0.51	0.50	0.54	0.57	0.13	
Education						
Less than a high school graduate	0.034	0.039	0.018	0.015	-0.56	0.46**
High school graduate or GED	0.30	0.20	0.16	0.15	-0.49	
Some college or associates degree	0.34	0.31	0.34	0.33	-0.04	
Bachelor's degree	0.22	0.28	0.29	0.30	0.35	
Graduate degree or professional degree	0.11	0.17	0.20	0.21	0.96	
Worker	0.67	0.70	0.69	0.63	-0.05	0.08
Hispanic	0.042	0.022	0.020	0.012	-0.71	0.15*
Asian/Pacific Islander	0.050	0.063	0.058	0.029	-0.42	0.10*
Black	0.059	0.046	0.050	0.034	-0.42	0.10*
Native American	0.016	0.0038	0.00	0.00	-1.00	0.13*
White	0.88	0.87	0.87	0.92	0.05	0.13*
Commute mode						
Private vehicle	0.92	0.89	0.88	0.91	-0.01	0.22*
Taxi	0.00080	0.00	0.00	0.00	-1.00	
Public transit	0.038	0.049	0.062	0.048	0.27	
Walk	0.029	0.024	0.016	0.017	-0.40	
Bike	0.0082	0.032	0.044	0.025	1.99	
Other	0.0086	0.0023	0.00	0.00	-1.00	
Commute time						
0-10 min	0.28	0.30	0.29	0.31	0.12	0.15*
10-20 min	0.32	0.29	0.32	0.31	-0.04	
20-30 min	0.21	0.19	0.18	0.16	-0.20	
30-60 min	0.17	0.20	0.19	0.18	0.09	
60-90 min	0.014	0.028	0.021	0.023	0.69	
90+ min	0.012	0.0057	0.0058	0.0072	-0.40	

(b) Household-level

Column No.	1	2	3	7	8	9
Dataset	*ACS MN*[4]	*NHTS MN*[5]	*NHTS HH reps*[5]	*Follow-up survey final predicted*[5]	*Percent change*[3]	*Effect size*[3]
Household size						
1	0.28	0.30	0.30	0.31	0.11	0.16*
2	0.36	0.38	0.38	0.41	0.14	
3+	0.36	0.32	0.32	0.28	-0.22	
Household income						
Less than $24,999	0.16	0.15	0.15	0.14	-0.14	0.20*
$25,000to $49,999	0.21	0.28	0.28	0.27	0.32	
$50,000 to $74,999	0.18	0.14	0.14	0.13	-0.26	
$75,000 to $99,999	0.14	0.15	0.15	0.16	0.14	
$100,000 to $149,999	0.17	0.15	0.15	0.17	-0.01	
More than $150,000	0.15	0.13	0.13	0.13	-0.09	
Vehicle ownership						
0	0.069	0.083	0.083	0.064	-0.07	0.09
1	0.30	0.30	0.30	0.30	0.01	
2	0.41	0.36	0.36	0.37	-0.08	
3+	0.23	0.25	0.25	0.26	0.14	
Homeowner	0.71	0.72	0.72	0.81	0.14	0.21*
No. of children						
0	0.72	0.73	0.73	0.77	0.07	0.12*
1	0.11	0.10	0.10	0.091	-0.15	
2	0.11	0.11	0.11	0.10	-0.12	
3+	0.066	0.063	0.063	0.044	-0.34	

Notes:
For each variable, the sum of the category shares might not equal 1 due to rounding errors.
[1] ACS individual weights are applied.
[2] NHTS individual weights are applied.
[3] Comparison between the population distribution and follow-up survey distribution (columns 1 and 5).
[4] ACS household weights are applied.
[5] NHTS household weights are applied.
* Small effect size (w = 0.10).
** Medium effect size (w = 0.30).
*** Large effect size (w = 0.50).

Table C4. Marginal distributions of selected variables in North Carolina

(a) Individual-level

Column No.	1	2	3	7	8	9
Dataset	*ACS NC*[1]	*NHTS NC*[2]	*NHTS HH reps*[2]	*Follow-up survey final predicted*[2]	*Percent change*[3]	*Effect size*[3]
Age						
18-24	0.13	0.12	0.051	0.028	-0.77	0.44**
25-34	0.17	0.16	0.15	0.11	-0.37	
35-44	0.17	0.17	0.17	0.14	-0.13	
45-54	0.18	0.16	0.17	0.17	-0.01	
55-64	0.16	0.19	0.22	0.24	0.44	
65+	0.20	0.20	0.23	0.31	0.55	
Gender						
Male	0.48	0.48	0.40	0.41	-0.14	0.14*
Female	0.52	0.52	0.60	0.59	0.13	
Education						
Less than a high school graduate	0.062	0.065	0.051	0.041	-0.33	0.54***
High school graduate or GED	0.33	0.23	0.18	0.16	-0.53	
Some college or associates degree	0.33	0.33	0.34	0.33	-0.01	
Bachelor's degree	0.18	0.22	0.25	0.26	0.41	
Graduate degree or professional degree	0.10	0.16	0.18	0.22	1.30	
Worker	0.59	0.60	0.59	0.53	-0.09	0.11*
Hispanic	0.073	0.075	0.078	0.060	-0.18	0.05
Asian/Pacific Islander	0.032	0.027	0.025	0.016	-0.52	0.09
Black	0.22	0.21	0.23	0.18	-0.17	0.09
Native American	0.018	0.010	0.010	0.0074	-0.60	0.08
White	0.72	0.72	0.71	0.78	0.08	0.12*
Commute mode						
Private vehicle	0.96	0.94	0.94	0.95	-0.01	0.15*
Taxi	0.0011	0.0046	0.0043	0.0028	1.55	
Public transit	0.011	0.017	0.019	0.022	0.99	
Walk	0.019	0.022	0.024	0.018	-0.06	
Bike	0.0022	0.0064	0.0074	0.0061	1.77	
Other	0.010	0.0058	0.0040	0.0044	-0.57	
Commute time						
0-10 min	0.25	0.25	0.26	0.25	0.01	0.11*
10-20 min	0.34	0.32	0.32	0.33	-0.04	
20-30 min	0.21	0.20	0.19	0.19	-0.11	
30-60 min	0.17	0.20	0.20	0.21	0.20	
60-90 min	0.015	0.020	0.019	0.019	0.25	
90+ min	0.013	0.014	0.011	0.011	-0.16	

(b) Household-level

Column No.	1	2	3	7	8	9
Dataset	*ACS NC*[4]	*NHTS NC*[5]	*NHTS HH reps*[5]	*Follow-up survey final predicted*[5]	*Percent change*[3]	*Effect size*[3]
Household size						
1	0.28	0.30	0.30	0.32	0.13	0.13*
2	0.36	0.35	0.35	0.38	0.07	
3+	0.36	0.35	0.35	0.30	-0.17	
Household income						
Less than $24,999	0.23	0.27	0.27	0.23	0.02	0.05
$25,000to $49,999	0.25	0.24	0.24	0.24	-0.05	
$50,000 to $74,999	0.18	0.17	0.17	0.18	-0.01	
$75,000 to $99,999	0.12	0.11	0.11	0.12	0.05	
$100,000 to $149,999	0.12	0.12	0.12	0.13	0.09	
More than $150,000	0.10	0.080	0.080	0.092	-0.06	
Vehicle ownership						
0	0.059	0.071	0.071	0.057	-0.04	0.06
1	0.32	0.34	0.34	0.33	0.04	
2	0.38	0.35	0.35	0.36	-0.07	
3+	0.24	0.24	0.24	0.25	0.07	
Homeowner	0.65	0.64	0.64	0.76	0.17	0.23*
No. of children						
0	0.73	0.71	0.71	0.76	0.04	0.09
1	0.12	0.14	0.14	0.12	0.01	
2	0.10	0.11	0.11	0.08	-0.17	
3+	0.052	0.050	0.050	0.038	-0.27	

Notes:

For each variable, the sum of the category shares might not equal 1 due to rounding errors.

[1] ACS individual weights are applied.

[2] NHTS individual weights are applied.

[3] Comparison between the population distribution and follow-up survey distribution (columns 1 and 5).

[4] ACS household weights are applied.

[5] NHTS household weights are applied.

* Small effect size (w = 0.10).

** Medium effect size (w = 0.30).

*** Large effect size (w = 0.50).

Table C5. Marginal distributions of selected variables in New York

(a) Individual-level

Column No.	1	2	3	7	8	9
Dataset	*ACS NY*[1]	*NHTS NY*[2]	*NHTS HH reps*[2]	*Follow-up survey final predicted*[2]	*Percent change*[3]	*Effect size*[3]
Age						
18-24	0.12	0.12	0.035	0.019	-0.85	0.49**
25-34	0.18	0.17	0.15	0.084	-0.55	
35-44	0.16	0.18	0.19	0.16	0.00	
45-54	0.17	0.17	0.19	0.19	0.08	
55-64	0.17	0.17	0.20	0.24	0.44	
65+	0.20	0.19	0.23	0.32	0.59	
Gender						
Male	0.48	0.47	0.43	0.45	-0.07	0.06
Female	0.52	0.53	0.57	0.55	0.06	
Education						
Less than a high school graduate	0.072	0.073	0.063	0.031	-0.56	0.58***
High school graduate or GED	0.32	0.21	0.17	0.16	-0.50	
Some college or associates degree	0.27	0.25	0.25	0.26	-0.02	
Bachelor's degree	0.20	0.23	0.25	0.23	0.17	
Graduate degree or professional degree	0.14	0.23	0.28	0.32	1.26	
Worker	0.072	0.073	0.063	0.031	-0.56	0.05
Hispanic	0.17	0.18	0.18	0.11	-0.35	0.16*
Asian/Pacific Islander	0.093	0.084	0.071	0.037	-0.60	0.19*
Black	0.16	0.16	0.17	0.10	-0.40	0.18*
Native American	0.010	0.0051	0.0065	0.0032	-0.68	0.07
White	0.67	0.73	0.72	0.84	0.26	0.37**
Commute mode						
Private vehicle	0.62	0.59	0.54	0.78	0.26	0.33**
Taxi	0.0064	0.0073	0.0052	0.0019	-0.70	
Public transit	0.29	0.31	0.35	0.17	-0.43	
Walk	0.064	0.066	0.078	0.035	-0.44	
Bike	0.0072	0.013	0.017	0.0078	0.08	
Other	0.0084	0.0072	0.0087	0.0072	-0.14	
Commute time						
0-10 min	0.18	0.20	0.17	0.23	0.23	0.20*
10-20 min	0.24	0.22	0.21	0.25	0.03	
20-30 min	0.20	0.17	0.17	0.16	-0.20	
30-60 min	0.29	0.29	0.32	0.24	-0.15	
60-90 min	0.062	0.090	0.094	0.089	0.45	
90+ min	0.025	0.031	0.031	0.031	0.27	

(b) Household-level

Column No.	1	2	3	7	8	9
Dataset	*ACS NY*[4]	*NHTS NY*[5]	*NHTS HH reps*[5]	*Follow-up survey final predicted*[5]	*Percent change*[3]	*Effect size*[3]
Household size						
1	0.30	0.32	0.32	0.29	-0.04	0.03
2	0.31	0.30	0.30	0.33	0.05	
3+	0.39	0.38	0.38	0.38	-0.01	
Household income						
Less than $24,999	0.21	0.24	0.24	0.17	-0.18	0.13*
$25,000to $49,999	0.19	0.18	0.18	0.18	-0.05	
$50,000 to $74,999	0.16	0.15	0.15	0.16	0.03	
$75,000 to $99,999	0.12	0.13	0.13	0.14	0.17	
$100,000 to $149,999	0.15	0.15	0.15	0.18	0.18	
More than $150,000	0.17	0.15	0.15	0.17	-0.04	
Vehicle ownership						
0	0.29	0.30	0.30	0.11	-0.61	0.43**
1	0.33	0.33	0.33	0.35	0.07	
2	0.26	0.23	0.23	0.33	0.27	
3+	0.12	0.13	0.13	0.21	0.71	
Homeowner	0.53	0.53	0.53	0.76	0.43	0.46**
No. of children						
0	0.74	0.71	0.71	0.72	-0.03	0.09
1	0.12	0.12	0.12	0.11	-0.03	
2	0.10	0.12	0.12	0.12	0.28	
3+	0.048	0.049	0.049	0.043	-0.10	

Notes:
For each variable, the sum of the category shares might not equal 1 due to rounding errors.
[1] ACS individual weights are applied.
[2] NHTS individual weights are applied.
[3] Comparison between the population distribution and follow-up survey distribution (columns 1 and 5).
[4] ACS household weights are applied.
[5] NHTS household weights are applied.
* Small effect size (w = 0.10).
** Medium effect size (w = 0.30).
*** Large effect size (w = 0.50).

Table C6. Marginal distributions of selected variables in Massachusetts

(a) Individual-level

Column No.	1	2	3	7	8	9
Dataset	*ACS MA*[1]	*NHTS MA*[2]	*NHTS HH reps*[2]	*Follow-up survey final predicted*[2]	*Percent change*[3]	*Effect size*[3]
Age						
18-24	0.13	0.10	0.057	0.024	-0.82	0.48**
25-34	0.18	0.22	0.19	0.11	-0.38	
35-44	0.15	0.13	0.13	0.11	-0.28	
45-54	0.18	0.18	0.19	0.19	0.08	
55-64	0.17	0.18	0.21	0.26	0.53	
65+	0.20	0.19	0.22	0.31	0.57	
Gender						
Male	0.48	0.47	0.47	0.43	-0.11	0.10*
Female	0.52	0.53	0.53	0.57	0.10	
Education						
Less than a high school graduate	0.051	0.037	0.029	0.022	-0.57	0.65***
High school graduate or GED	0.29	0.19	0.14	0.11	-0.61	
Some college or associates degree	0.26	0.22	0.20	0.20	-0.22	
Bachelor's degree	0.23	0.26	0.27	0.28	0.23	
Graduate degree or professional degree	0.17	0.30	0.36	0.38	1.26	
Worker	0.63	0.65	0.66	0.59	-0.06	0.08
Hispanic	0.10	0.10	0.09	0.05	-0.46	0.15*
Asian/Pacific Islander	0.071	0.085	0.066	0.040	-0.44	0.12*
Black	0.083	0.069	0.090	0.055	-0.33	0.10*
Native American	0.0064	0.00	0.00	0.00	-1.00	0.08
White	0.82	0.83	0.83	0.89	0.09	0.18*
Commute mode						
Private vehicle	0.82	0.74	0.73	0.83	0.02	0.16*
Taxi	0.0026	0.0093	0.0092	0.0021	-0.19	
Public transit	0.11	0.17	0.18	0.13	0.22	
Walk	0.051	0.065	0.068	0.025	-0.52	
Bike	0.0091	0.0099	0.0061	0.0023	-0.75	
Other	0.011	0.0055	0.0055	0.0084	-0.24	
Commute time						
0-10 min	0.21	0.19	0.17	0.19	-0.10	0.33**
10-20 min	0.27	0.24	0.22	0.23	-0.15	
20-30 min	0.20	0.21	0.19	0.15	-0.29	
30-60 min	0.26	0.27	0.32	0.33	0.24	
60-90 min	0.044	0.062	0.058	0.078	0.77	
90+ min	0.014	0.029	0.034	0.038	1.78	

(b) Household-level

Column No.	1	2	3	7	8	9
Dataset	*ACS MA*[4]	*NHTS MA*[5]	*NHTS HH*[5]	*Follow-up survey final predicted*[5]	*Percent change*[3]	*Effect size*[3]
Household size						
1	0.29	0.34	0.34	0.34	0.19	0.16*
2	0.33	0.34	0.34	0.35	0.05	
3+	0.38	0.32	0.32	0.31	-0.19	
Household income						
Less than $24,999	0.17	0.19	0.19	0.17	-0.05	0.11*
$25,000to $49,999	0.17	0.20	0.20	0.19	0.14	
$50,000 to $74,999	0.15	0.14	0.14	0.14	-0.03	
$75,000 to $99,999	0.12	0.11	0.11	0.13	0.06	
$100,000 to $149,999	0.18	0.18	0.18	0.19	0.10	
More than $150,000	0.22	0.18	0.18	0.18	-0.16	
Vehicle ownership						
0	0.12	0.15	0.15	0.09	-0.32	0.13*
1	0.36	0.36	0.36	0.35	-0.01	
2	0.36	0.35	0.35	0.41	0.12	
3+	0.16	0.13	0.13	0.16	0.00	
Homeowner	0.62	0.61	0.61	0.76	0.23	0.30**
No. of children						
0	0.73	0.75	0.75	0.77	0.04	0.12*
1	0.12	0.11	0.11	0.10	-0.17	
2	0.11	0.11	0.11	0.12	0.07	
3+	0.043	0.034	0.034	0.022	-0.49	

Notes:
For each variable, the sum of the category shares might not equal 1 due to rounding errors.
[1] ACS individual weights are applied.
[2] NHTS individual weights are applied.
[3] Comparison between the population distribution and follow-up survey distribution (columns 1 and 5).
[4] ACS household weights are applied.
[5] NHTS household weights are applied.
* Small effect size (w = 0.10).
** Medium effect size (w = 0.30).
*** Large effect size (w = 0.50).

APPENDIX D. SAMPLE SELECTION MODEL

The sample selection (SS) model was proposed by Heckman (1976) to address selection biases in modeling. The SS model consists of two sub-models, selection and outcome models. The selection model reflects the likelihood of a person to be included (in our case, "self-selected") into the sample experiencing the outcome, while the outcome model explains the variable of interest (a continuous variable, in this classic form of the SS model). In Chapter 7, the selection model explains respondents' participation in the GDOT survey using the full NHTS Georgia subsample (i.e., NHTS_R and NHTS_DNR), while the outcome model explains the vehicle-miles driven (VMD) collected through the GDOT survey for the overlapped sample (i.e., NHTS_R). The selection and outcome models are defined as follows:

$$y_i^{S^*} = \boldsymbol{z_i}\boldsymbol{\gamma} + \varepsilon_i^S, \tag{1}$$

$$y_i^{O^*} = \boldsymbol{x_i}\boldsymbol{\beta_N^{SS}} + \varepsilon_i^O, \tag{2}$$

$$y_i^S = \begin{cases} 0, & if\ y_i^{S^*} < 0 \\ 1, & otherwise, \end{cases} \tag{3}$$

$$y_i^O = \begin{cases} 0, & if\ y_i^S = 0 \\ y_i^{O^*}, & otherwise, \end{cases} \tag{4}$$

where $y_i^{S^*}$ is the continuous latent variable indicating the tendency for individual i to participate in the GDOT survey; y_i^S is the observed choice to participate in the GDOT survey; $y_i^{O^*}$ is individual i's VMD; y_i^O is individual i's *observed* VMD, which is $y_i^{O^*}$ for respondents to the GDOT survey, and unobserved and therefore undefined (specified as "0" in keeping with convention) otherwise; $\boldsymbol{z_i}$ and $\boldsymbol{x_i}$ are vectors of explanatory variables for the selection and outcome models, respectively; $\boldsymbol{\gamma}$ and $\boldsymbol{\beta}_{\boldsymbol{N}}^{\boldsymbol{SS}}$ are the corresponding coefficient vectors; and ε_i^s and ε_i^O are error terms that capture the unobserved effects in the two models. As is standard, we assume that the error terms follow a bivariate normal distribution:

$$\begin{pmatrix} \varepsilon^S \\ \varepsilon^O \end{pmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & \sigma^2 \end{pmatrix}\right). \tag{5}$$

Using the properties of a bivariate normal distribution, the log-likelihood is written as

$$\begin{aligned} \ell\left(\widehat{\boldsymbol{\gamma}}, \widehat{\boldsymbol{\beta}}, \hat{\rho}, \hat{\sigma}\right) = & \sum_{i:y_i^S=0} \log\left(\Phi(-\boldsymbol{z_i}\widehat{\boldsymbol{\gamma}})\right) \\ & + \sum_{i:y_i^S=1} \log\left[\Phi\left(\frac{\boldsymbol{z_i}\widehat{\boldsymbol{\gamma}} + \frac{\hat{\rho}}{\hat{\sigma}}\left(y_i^O - \boldsymbol{x_i}\widehat{\boldsymbol{\beta}}_{\boldsymbol{N}}^{\boldsymbol{SS}}\right)}{\sqrt{1-\hat{\rho}^2}}\right) - \log\sqrt{2\pi}\hat{\sigma} - \frac{\left(y_i^O - \boldsymbol{x_i}\widehat{\boldsymbol{\beta}}_{\boldsymbol{N}}^{\boldsymbol{SS}}\right)^2}{2\hat{\sigma}^2}\right], \end{aligned} \tag{6}$$

where $\Phi\,(\cdot)$ represents the cumulative univariate standard normal distribution function.

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